Direct Marketing Strategies and Farmers' Technical Efficiency in U.S. Agriculture

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Abstract:

Farmers are increasingly using direct marketing strategies that include farmers' markets and community supported agriculture arrangements to connect with consumers who prefer locally produced food. We examine the relationship between the increasing use of direct marketing strategies and technical efficiency, using stochastic frontier analysis method. The results show that, on average, the farmers that use direct marketing strategies are less technically efficient compared to the farmers that do not. However, this result is reversed for the largest quantile of growers, on average those who use direct marketing strategies are more technically efficient than those not.

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Keywords: productivity; direct marketing; local food; technical efficiency; stochastic frontier analysis

JEL: Q12, Q13

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1. Introduction

The use of direct marketing (DM) strategies by farmers, which include roadside stores, on-farm stores, farmers market, regional distributors, state branding programs, direct sales to local grocery stores, restaurants or outlets and community supported agriculture (CSA) has been increasing. Brown and Miller (2008) state that the number of farmers markets increased by 150 percent between 1994 and 2006. The number of farms that directly sold their agricultural products to individuals increased by 17 percent, while the value of DM sales increased by about 50 percent between 2002 and 2007 (Park *et al.* 2014). The growth in use of DM is attributed to among others, the outward shift in the demand for healthy food, consumers' willingness to pay (WTP) a premium for locally produced food, consumers' desire to support local farmers, and U.S. Government support for DM through programs such as "Know Your Farmer, Know Your Food."

On one hand, the DM strategies can provide important avenues for farmers to sell their products directly to consumers and earn a high price, might act as might also act as an important source of a stable market and they can also help farmers get direct feedback from consumers which they can use to improve their operations. On the other hand, farmers who participate and engage in alternative marketing arrangements spend valuable labor time attending to the DM markets compared to farmers that have traditional and indirect marketing arrangements. The lost valuable labor may affect the on-farm operations. Therefore, it is important to investigate the effect of DM strategies on the productivity of the farm.

The objective of this study is to examine the relationship between farmers' use of DM strategies on their technical efficiency (TE), a measure of managerial ability using a nationally representative farm-level dataset from the US Department of Agriculture's Agricultural Resource Management Survey (ARMS) of 2015. Specifically, we seek to answer the following research question: what is the relationship between using DM strategies and technically efficiency? We test two hypotheses that emerge which are: 1) Given the increase in the number of farmers markets and the multiple DM channels available, farmers participate at more than one farmers' market each week and generally pursue multiple DM channels. The opportunity cost of time spent in DM channels is time not spent managing on-farm production. This has potential to negatively affect farmers' management ability. 2) Prior studies that include Gillespie *et al.* (2007), find that farmers' markets encourage the production of diversified food products as a mechanism to attract a greater variety of consumers. As farmers diversify, they potentially engage in production of commodities they might not have the management capability or expertise for which in turn has potential to negatively affect their TE.

Prior studies focus on consumer attributes and how they influence their decision to buy through DM channels. Darby *et al.* (2008) find that consumers are willing to pay more for locally grown products. Uematsu and Mishra (2011) and Park *et al.* (2014) attempt to fill the gap in the literature by focusing on the producer side, by examining the factors that influence producers' (farmers) decision to use DM strategies and how they subsequently affect the farm business income. Uematsu and Mishra (2011) find a negative impact of DM strategies (farmers' markets and roadside stores) on gross cash farm income; Park (2015) find a negative relationship between involvement in DM and farm sales with smaller operations more severely impacted than larger operations. Park *et al.* (2014) find that farmers with broader marketing skills are likely to increase their sales through DM strategies. Additionally, Low *et al.* 2015 note that direct t consumer sales boosts chances of maintaining positive sales and increased survivability rate of farms between 2007 and 2012. While none of these studies examines TE of farmers engaged in DM, which is the objective of this study, there is no consensus on the impact of DM strategies on sales and/or farm income. Prior literature that find a negative relationship between using DM strategies and farm sales highlights that the marginal cost of DM outweighs the marginal benefit. This warrants the present study to further investigate the source of the high marginal cost associated with DM strategies. As Tauer and Mishra (2006) note, inefficiency is the source of higher production costs for small farms and improvement in efficiency decreases costs (Mosheim and Lovell 2009).

Related prior studies that also make use of the farm-level ARMS data are Detre *et al.* (2011) and Low and Vogel (2011). However, Park *et al.* (2014) offer a critic of these studies for their failure to examine management and marketing skills and highlight the crucial role of these two in farmers' sales. Therefore, our study attempts to fill this gap by looking at the effect of direct marketing strategies on the management ability.

Our main argument in this study is that farming is already an intellectually challenging endeavor. Adding supply chain management and the additional burden from DM could be profound and in turn negatively impact on-farm production management. We use the 2015 nationally representative ARMS dataset to examine whether there are differences in TE between those engaged in DM strategies and those not and whether DM strategies intensification (measured by share of direct marketing sales to total sales) is inversely related to TE. We control for the diversification demands of DM strategies using the Herfindahl index. There is no research, that we are aware of, that has examined the relationship between using DM strategies and TE or productivity in general.

The rest of the paper is organized as follows. In section 2 we present the theoretical framework that shows the relationship between use of DM and TE. In section 3 we present the stochastic frontier analysis (SFA) empirical model and our estimation strategy. Data and summary statistics are presented in section 4. This is followed by estimations and empirical results in section 5, and section 6 concludes.

2. Theoretical framework

We develop a model that captures the farm participation in direct marketing and traditional marketing schemes. We assume that total factor productivity is given by $0 < \gamma \leq 1$, in which $\gamma < 1$ implies technical inefficiency and $\gamma = 1$, implies technical efficiency . We also assume that Following a similar approach to Kugler and Verhoogen (2012), we assume production of a quality agricultural output, q, requires two sources of inputs, quality inputs c, and labor. The unit cost of labor is w. The labor, $l \in (0,1)$ is allocated to DM schemes, and $1 - l$ is allocated to production. The participation in the traditional marketing schemes does not require the allocation of labor. The share of the quality output sold through DM schemes is α, and $1 - \alpha$ is sold via traditional marketing schemes. The costs of accessing DM channels is given by $v^d(l)$ per unit of output, in which $v_l' > 0$, and $v_{ll}'' < 0$, while costs of accessing traditional marking channel is given by v^r per unit of output. The production function for the quality output is, $y = \gamma f(1 - l, c)$.

Following Chiang, Chhajed, and Hess (2003), if a product is sold in the traditional market, then the price is $P^r(c)$, and the consumer valuation is c. If the product is sold under

DM, then the price is given by $P^d(c^d)$ the consumer valuation is $c^d = \theta c$, where $\theta > 0$ captures the value that consumers attach to DM schemes. Therefore it should be that consumers whose valuation is $c - P^r \geq 0$, would consider buying from the traditional market. The consumer whose valuation c equals to P^r is indifferent to buying from the retailer, or not at all. The consumers whose valuation is $\theta c - P^d \geq 0$, would consider buying from the direct market channel. The consumer whose valuation c^d equals to P^d/θ is indifferent to buying from the direct market, or not at all. If $c - P^r \geq \theta c - P^d$, then the traditional market is weakly preferred to the DM channel. The consumer whose valuation c^{rd}, equals to $(P^r - P^d)/(1-\theta)$ is indifferent between the channels, and if the valuation exceeds this, they prefer the retailer. The expected farm profits are therefore given by,

(1) $[P^r(c) - v^r]\gamma f(1, c) - w - c,$

if the products are sold under the traditional marketing schemes, and

(2) $[P^d(c) - v^d(l)]\gamma f(1-l, c) - w(1-l) - c,$

if the products are sold under DM schemes.

We therefore solve for the optimal condition under three possible scenarios, that is when there is participation on either market only, or when there is simultaneous participation on both markets. We consider the interior solutions only, i.e. when the consumer valuations are equal to the price.

If the farm participates in the traditional marketing schemes only, it solves,

$$\max_c [P^r(c) - v^r]\gamma f(1, c) - w - c,$$

subject to $c - P^r = 0$, such that,

(3) $\gamma f + (c - v^r)\gamma f_1' = 1, l = 0.$

If the farm participates in DM schemes only, it solves

$$\max_{c,l}[P^d(c) - v^d(l)]\gamma f(1-l, c) - w(1-l) - c,$$

subject to $\theta c - P^d \geq 0$, such that,

(4) $\theta\gamma f + (\theta c - v^d)\gamma f_1' = 1, [\theta c - v^d]\gamma f_2' + v_l'\gamma f = w.$

If the farm participates in both markets, it solves,

$$\max_{c,l}(1-\alpha)([P^r(c) - v^r]\gamma f(1-l, c) - w - c) +$$

$$\alpha([P^d(c) - v^d(l)]\gamma f(1-l, c) - w(1-l) - c),$$

subject to $c = (P^r - P^d)/(1-\theta)$, such that,

(5) $(1-\alpha)\left[(1-\theta)\gamma f + \left((1-\theta)c + P^d\right)\gamma f_1'\right] +$

$\alpha\left[-(1-\theta)\gamma f + \left(P^r - (1-\theta)\right)\gamma f_1'\right] = 1$, and

$-(1-\alpha)(P^r - v^r)\gamma f_2' + \alpha(-[P^d - v^d]\gamma f_2' - v_l'\gamma f + w) = 0.$

A comparison of (3) and (4) shows that the utilization of quality inputs and labor is different under the two marketing arrangements. The implicit function of the marginal product of the quality inputs for the traditional and DM schemes is given, respectively, by $f_1'^r = \frac{1-\gamma f^r}{\gamma(c^r - v^r)}$, and $f_1'^d = \frac{w - v_l'\gamma f^d}{\gamma(\theta c^d - v^d)}$. Therefore we have DM scheme being more efficient compared to the traditional marketing scheme, that is $f_1'^r > f_1'^d$, if and only if $\frac{1-\gamma f^r}{c^r - v^r} > \frac{w - v_l'\gamma f^d}{(\theta c^d - v^d)}$. Similarly, the traditional marketing scheme is more efficient compared to DM scheme, iff $\frac{1-\gamma f^r}{c^r - v^r} > \frac{w - v_l'\gamma f^d}{(\theta c^d - v^d)}$. In other words, the divergence is influenced by the value that the consumers attach on the direct market mechanisms compared to the traditional schemes. Thus if the preference parameter θ is below the threshold, $\frac{(w - v_l'\gamma f^d)}{(1-\gamma f^r)}\frac{(c^r - v^r)}{c^d} + \frac{v^d}{c^d}$, then the DM scheme is more efficient compared to the traditional marketing scheme. From the model, the divergence between the two systems is from two sources: the first is that consumers place a higher valuation on goods marketed through direct market schemes compared to traditional schemes. The second is that DM schemes have an additional cost, in which some of the labor is sacrificed from production into promoting these schemes. This implies that there is foregone output from participating in DM schemes. The former is a benefit to the farmer and it increases revenues encouraging increased production, while the later reduces productivity and output, negatively affecting revenues. Thus depending on the magnitude of these opposing forces, DM schemes can either be superior or inferior to traditional schemes. From the FOC, the efficiency between the two marketing systems is ambiguous. The FOC do not contain sufficient information that can help to compare the two systems.

In order to determine the relationship between participation in DM strategies and technical efficiency, we use the implicit function theorem (IFT) to find the effect of exogenous changes in productivity on the supply of labor to DM strategies.

$\theta\gamma f + (\theta c - v^d)\gamma f_1' = 1$, $[\theta c - v^d]\gamma f_2' + v_l'\gamma f = w$.

$$\begin{bmatrix} 2\theta\gamma f_1' + (\theta c - v^d)\gamma f_{11}'' & \theta\gamma f_2' + (\theta c - v^d)\gamma f_{12}'' + v_l'\gamma f_1' \\ v_l'\gamma f_1' + (\theta c - v^d)\gamma f_{12}'' + \theta\gamma f_2' & -v_{ll}''\gamma f + 2v_l'\gamma f_2' + (\theta c - v^d)\gamma f_{22}'' \end{bmatrix} \begin{bmatrix} \frac{\partial\gamma}{\partial c} \\ \frac{\partial\gamma}{\partial l} \end{bmatrix} =$$

$$-\begin{bmatrix} \theta f + (\theta c - v^d) f_1' \\ v_l' f + (\theta c - v^d) f_2' \end{bmatrix}$$

The second order sufficient condition (*sosc*) for a maximum on equation (4) is such that $2\theta\gamma f_1' + (\theta c - v^d)\gamma f_{11}'' > 0$, and that $[2\theta f_1' + (\theta c - v^d) f_{11}''][-v_{ll}''\gamma f + 2v_l'\gamma f_2' + (\theta c - v^d)\gamma f_{22}''] - [\theta\gamma f_2' + (\theta c - v^d)\gamma f_{12}'' + v_l'\gamma f_1']^2 < 0$. Therefore, we have

$$\frac{\partial \gamma}{\partial l} = \begin{bmatrix} 2\theta\gamma f_1' + (\theta c - v^d)\gamma f_{11}'' & -(\theta f + (\theta c - v^d)f_1') \\ v_l'\gamma f_1' + (\theta c - v^d)\gamma f_{12}'' + \theta\gamma f_2' & -(v_l' f + (\theta c - v^d)f_2') \end{bmatrix} / sosc$$

This implies that we have $\frac{\partial \gamma}{\partial l} = -[2\theta\gamma f_1' + (\theta c - v^d)\gamma f_{11}''][(v_l' f + (\theta c - v^d)f_2')] + [v_l'\gamma f_1' + (\theta c - v^d)\gamma f_{12}'' + \theta\gamma f_2'][(\theta f + (\theta c - v^d)f_1')]$. That is we have an increase in productivity associated with a decrease in labor allocated to DM strategies if $\frac{[v_l'\gamma f_1' + (\theta c - v^d)\gamma f_{12}'' + \theta\gamma f_2']}{[(v_l' f + (\theta c - v^d)f_2')]} > \frac{[2\theta\gamma f_1' + (\theta c - v^d)\gamma f_{11}'']}{[(\theta f + (\theta c - v^d)f_1')]}$, i.e. if the returns to marginal product of labor from productivity increases is greater than the return to marginal product of inputs from productivity increases. That is when the elasticity of substitution between the labor and inputs from productivity changes is greater than 1. Similarly, an increase in productivity is associated with an increase in the labor allocated to DM strategies if Fthe elasticity of substitution between labor and other inputs from productivity changes less than a unit. Therefore, in order to determine the relationship between labor allocation and efficiency, there is need to appeal to an empirical analysis.

3. Empirical model

We use stochastic frontier analysis (SFA) to estimate TE and also simultaneously estimate the impact of DM strategies on the estimated TE. We specify the production technology as a stochastic production frontier developed by *Aigner et al*. (1977) and Meeusen and van den Broeck (1977):

(6) $Q_i = f(\boldsymbol{X_i}; \boldsymbol{\beta}).\exp(V_i - U_i)$,

where i is the index for the farm; Q is gross value of farm output;[1] $\boldsymbol{X}$ is a vector of all productive inputs; $\boldsymbol{\beta}$ is a vector of parameters to be estimated; V_i is a random noise stochastic term that can increase or decrease output; U_i is a nonnegative stochastic inefficiency term; $V_i - U_i = \varepsilon_i$ is the error term.

Technical efficiency for the ith farm (TE_i) is defined as:

$$(7) \qquad TE_i = \frac{Q_i}{f(\boldsymbol{X}_i;\boldsymbol{\beta}) \cdot \exp(V_i)} = \exp(-U_i).$$

Equation (7) shows that TE_i is the ratio of the observed output for the ith farm to feasible output on the production frontier and $0 \leq TE_i \leq 1$, where 1 means the farm is technically efficient. We estimate equation (6) using the translog functional form due to its flexibility. The model we estimate is:

$$(8) \qquad \ln(Q_i) = \beta_0 + \sum_{k=1}^{4} \beta_k \ln(X_{ik}) + \frac{1}{2}\sum_{k=1}^{4}\sum_{j=1}^{4} \beta_{kj}\, ln(X_{ik}) \ln\left(X_{ij}\right) + \gamma_i + \sum_{k=1}^{2} \theta_k Y_{ik} + \sum_{k=1}^{12} \phi_k W_{ik} + V_i - U_i,$$

where $\boldsymbol{X}_i$ includes land, labor, capital, and other inputs; γ_i represents regional fixed effects to control for unobserved regional effects; Y_{ik} includes human capital measures age and education; W_{ik} includes variables for high quality and medium quality soils, road density, highway access, annual maximum temperature deviation from a 30 year average, average temperature for the months of July and August, and deviations from 30 year average monthly precipitation for May, June, July, August, and September. The technical inefficiency effects are defined as:

[1] Gross value of farm output is used instead of quantities of output due to unsuitability of the stochastic production frontiers to work with multiple outputs. In cases where there are multiple outputs, one option is to use value of all output (Battese and Coelli 1995).

(9) $U_i = \alpha_0 + \alpha_1 DM_i + \alpha_2 H_i + \sum_{k=3}^{7} \alpha_k Z_{ik}$,

where *DM* includes two different measures: DM intensity (share of direct sales) and indicator variable for use of DM; *H* is a Herfindahl index of commodities sold; $\boldsymbol{Z}_i$ are factors that may impact farmers' management ability including education, age, farming full-time, and use of production contracts. The idiosyncratic variation in output is defined as:

(10) $V_i = \eta_0 + \sum_{k=1}^{12} \eta_k W_{ik}$,

where W_{ik} is defined as above for equation (8).

The standard assumptions on V_i and U_i are: $E[V_i] = 0, \forall i, E[U_i] > 0; E[V_i^2] = \sigma_v^2, E[U_i^2] = \sigma_u^2; E\left[V_i V_j\right] = E\left[U_i U_j\right] = 0, \forall\ i$ and $j \neq i$; and correlation between V_i and U_i is assumed to be zero (Coelli *et al.* 2005). With $V_i \sim N$, $U_i \sim N^+$distributional assumptions, the log-likelihood function for equation (8) is:

(11) $lnL(Q_i|\boldsymbol{\beta}, \sigma, \lambda) = \sum_{i=1}^{N}\{0.5ln(2/\pi) - ln\sigma + ln\Phi(-\varphi_i) - \varepsilon_i^2/2\sigma^2\}$,

where $\sigma^2 = (\sigma_u^2 + \sigma_v^2), \lambda = \sigma_u/\sigma_v, ; \varepsilon_i = V_i - U_i = Q_i - f(\boldsymbol{X}_i;\ \boldsymbol{\beta}), \varphi_i = \varepsilon_i \lambda/\sigma$, and $\Phi(\varphi)$ is the standard normal cumulative distribution function. From estimation of equation (8) we are able to determine ε_i. To obtain the inefficiency component U_i, we calculate the conditional mean (Jondrow *et al.* 1982):

(12) $E[U_i|\varepsilon_i] = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi(\varphi_i)}{1-\Phi(\varphi_i)} - \varphi_i\right]$.

Similar to Key and Sneeringer (2014), we estimate equation (8) using the single-step approach by substituting for U_i with equation (9). Following Lien, Kumbhakar, and Hardaker (2010), Key and Sneeringer (2014) all logged variables were standardized to have means of zero (i.e., each observation for the variable was divided by its geometric mean) so that the estimated input coefficients (linear terms) can be interpreted as output elasticities evaluated at the sample means. Prior to data transformation (taking logs and standardizing), a one was added to all observations for variables that included any zero values. Equation (8) was estimated using the frontier command in Stata 15 and our parameter of interest is α_1 in the U_i term (equation 9). We hypothesize a positive sign for α_1, i.e., a negative association between DM and TE.

4. Data

The 2015 ARMS farm-level survey dataset contains information about the farm operator characteristics, farm production technology and resource usage, and the marketing strategies used by the farm. Previous research indicates that direct market sales are concentrated in fruit and vegetable producing regions (Low and Vogel 2011). In order to compare like farms to like, we subset the 2015 ARMS sample to farms that sold fruits or vegetables. This sub-sample includes all of the 647 farms that directly marketed agricultural products and 981 farms that did not. Summary statistics for the combined sample are presented in Table 1.

Output is measured in total value of product sold and includes cash sales from fruits and vegetables, other crops, livestock and milk, and product sold through marketing or production contracts. Land and labor inputs are measured in acre and hour quantities. Other inputs measured by expenditures in dollars include livestock inputs including purchased or leased animals, feed, bedding, and medical supplies; seed; fertilizer; chemicals; irrigation; fuel inputs including electricity and utilities; repair inputs including supplies and maintenance; financial inputs including insurance, debt interest, and property tax; and capital inputs including dwellings, buildings, orchards, mineral rights, vehicles, and stock in cooperatives. Operator human capital is given by principal operator's college education status and age.

Marketing choice variables include two measures of direct marketing practices and a Herfindahl index of production diversification. The first measure of direct marketing is an indicator variable that is one if the farm sells product directly to individual consumers, retail outlets or regional distributors that sold directly to individual consumers, or institutions that served directly to consumers, and zero otherwise. The alternative measure of direct marketing is the share of total sales comprised of direct market sales. The measure of production diversification is given by a Herfindahl index, $H = 1 - \sum_i s_i^2$ where s_i is the share of gross sales from the *i*th activity of five commodity groups as in Park (2015): major field crops including grains, minor field crops including oilseeds and dry beans, fruit and greenhouse crops, vegetables including potatoes and sweet potatoes, and livestock and dairy products. We also include indicator variables for whether the operator farms full-time and uses production contracts to market their product.

We also include a set of county-level temperature, precipitation, soil quality, road density, and highway access variables to account for idiosyncratic variation in output that should not be measured as technical inefficiency. Temperature measures for average monthly maximum, the deviation from the 30-year average temperature in July, and the deviation from the 30-year average temperature in August come from the PRISM climatological data. We obtain deviations from 30-year precipitation averages for the months of May, June, July, August, and September from PRISM as well. Soil quality measure are aggregated into percentage of high quality and medium quality soils from eight soil quality measures in the USDA, National Resource Conservation Service's Land-capability Classification database. The measure of highway access comes from ESRI/Teleatlas 2006-2007. We measure county-level population density using an index constructed from the

2010 Census by ERS. To capture regional fixed effects we generate a set of indicator variables from the Cartesian product of states, which capture differences that may arise from political boundaries such as agricultural or environmental policy, and 20 ERS Land Resource Regions, which group areas with similar physiographic, soil, and climatic traits.

5. Estimations and results

Parameter estimates for four stochastic frontier models are presented in Table 2. The first model contains estimates of the stochastic frontier using a translog specification of the technology function without estimating either U or V, equations (9) and (10) respectively. The ratio of the decomposed portions of the error $\lambda = U/V$ equals 2.58, which demonstrates that the proportion of the error attributable to differences in efficiency exceeds the proportion of the error attributable to idiosyncratic differences in the estimation of total sales. In other words, we are able to identify a technology frontier and estimate deviations from it.

The second model adds an estimating equation for U while the third model adds estimating equations for both U and V. Parameter estimates in models 2 and 3 are extremely similar, and none of the estimated parameters in the unreported V equation in model 3 are statistically significant at the 5 percent level. This indicates that the model is correctly proportioning deviations from the technology frontier into technical inefficiency and error from other idiosyncratic factors.

The estimate for our main parameter of interest, 0.43, is positive and statistically significant at the 1 percent level in both models two and three. This finding indicates a negative relationship between intensity in use of DM strategies and technical efficiency. That is, firms with a higher share of direct sales are less efficient on average. As farmers devote more time off-farm to market their farm produce, the trade-off is time to manage their farming enterprises. This finding confirms our original hypothesis that despite the higher premium farmers potentially earn by marketing their produce through these DM strategies, these strategies are counterproductive [they may suffer losses from declines in efficiency].

The finding that an increase in the use of direct marketing strategies results in a decrease in technical efficiency highlights the impact on farm management when farmers reallocate their labor from production to marketing. This result is similar to studies that found a negative impact that working off-farm has on technical efficiency. Despite some studies showing that farms that use direct marketing strategies have a higher survivability, it is plausible that the premium consumers are willing to pay for local produce and the elimination of the middleman could be providing a cushion to protect the farmers' inefficiencies. This implies that as farmers intensify their use of direct marketing strategies, there is need for modification in their production and management strategies to compensate for the increased time they spend marketing their produce.

Using model 3 as our base model, production inputs land and labor are positive and statistically significant at the 1 percent level. Their elasticities are 0.30 and 0.19, respectively. As more land and labor is used, total sales are expected to increase. This could be a result of both fruits and vegetables being land and labor intensive contrary to other farm enterprises. Capital is negative and statistically significant with an elasticity of 0.43. A plausible explanation for the negative elasticity of capital is that as more capital is used while land, labor and other inputs are held constant, there is diminishing returns to capital.

In addition, the high cost of capital potentially crowds out investment in other production inputs such as land and labor. Other inputs are statistically insignificant.

For the farm household and management characteristics, neither age, college education, nor diversity of farm output given by the Herfindahl index is statistically significant. However, both farming full-time and using production contracts are indicative of greater technical efficiency, with negative and statistically significant parameter values at the 5 percent level. Being a full-time farmer is associated with a decrease in technical inefficiency and hence an increase in TE. As farmers devote all their time and energy to managing their farm business, the added benefit is improvement in their farm production management. Similarly, engaging in production contracts enhances farm management as farmers have a guaranteed market and can fully devote their time and effort in ensuring that they meet their end of the production contract bargain.

We compare predicted technical inefficiency of farms using direct marketing strategies and those not, for three size cohorts in Table 3. We divide the sample into the lowest third in terms of dollar value of sales, the middle third, and highest third. For the lowest third there is a statistically significant difference in mean efficiency, with direct marketers being less efficient than wholesale marketers. No statistically significant difference is found for the middle third, but the association reverses for the highest third—direct marketers on average are more technically efficient than wholesalers. This result ties back to prices in the theoretical model. Highly efficient firms that produce equal amounts of outputs from equal amounts of inputs, will have different measures of technical efficiency when one firm obtains a price premium by selling in the direct market. In Figure 1, the tail of the histogram of efficiency predictions is fatter for direct marketers compared to wholesalers, Figure 2, indicating lower technical efficiency on average. However, as the histograms show, there are quite a few highly efficient farms that use direct marketing and some highly inefficient farms that do not.

To further explore how using direct marketing strategies may impact efficiency, we estimate a probit model with an indicator variable of direct marketing use as dependent variable and predicted efficiencies from model 3 as an independent variable along with age, college, Herfindahl, full-time farmer, production contracts, and farm inputs. Results are presented in Table 4. We find efficiency to have a statistically significant effect at the 0.1 percent level on direct marketing, decreasing the likelihood of using direct marketing strategies. Having more land decreased the likelihood while having more labor increased the likelihood.

6. Conclusions

The use of direct marketing (DM) strategies by farmers has been increasing. DM strategies includes roadside stores, on-farm stores, farmers market, regional distributors, state branding programs, direct sales to local grocery stores, restaurants or outlets and community supported agriculture (CSA). In this paper we examine the impact of farmers' use of DM strategies on their technical efficiency (TE) (measure of managerial ability) using a nationally representative farm-level dataset from the 2015 Agricultural Resource Management Survey (ARMS). Our main argument is that farming is already an intellectually challenging endeavor. Adding supply chain management and the additional burden from DM particularly for small, beginning, young, and less educated farmers could be profound and in turn negatively impact on-farm production management.

We develop a theoretical model that captures the farm participation in direct marketing and traditional marketing schemes. Through this theoretical analysis, we show that either marketing scheme can be efficient and the divergence in efficiency between these two is from two sources: the first is that consumers place a higher valuation on goods marketed through direct schemes compared to traditional schemes. The second is that DM schemes have an additional cost, in which some of the labor is sacrificed from production into promoting these schemes potentially resulting in forgone output. While the former is a benefit to the farmer as it encourages production by increasing revenue, the latter is a cost as it potentially reduces productivity and output.

Empirical results support our hypothesis. Using a stochastic frontier analysis, we find a negative relationship between use of DM strategies and technical efficiency. Empirical results show as farmers reallocate their labor from production to marketing their productivity suffers. This finding is similar to studies that found a negative impact that an increase in off-farm has on technical efficiency. Results from this study suggest that as farmers intensify their use of direct marketing strategies, there is need for modification in farm production and management strategies to compensate for the increased time farmers spend marketing their produce. Further, increased farmer education on successful marketing strategies that minimize counter productivity could prove helpful in ensuring that farmers minimize the cost associated with direct marketing.

Figure 1. Technical efficiency distribution for those using direct marketing strategies

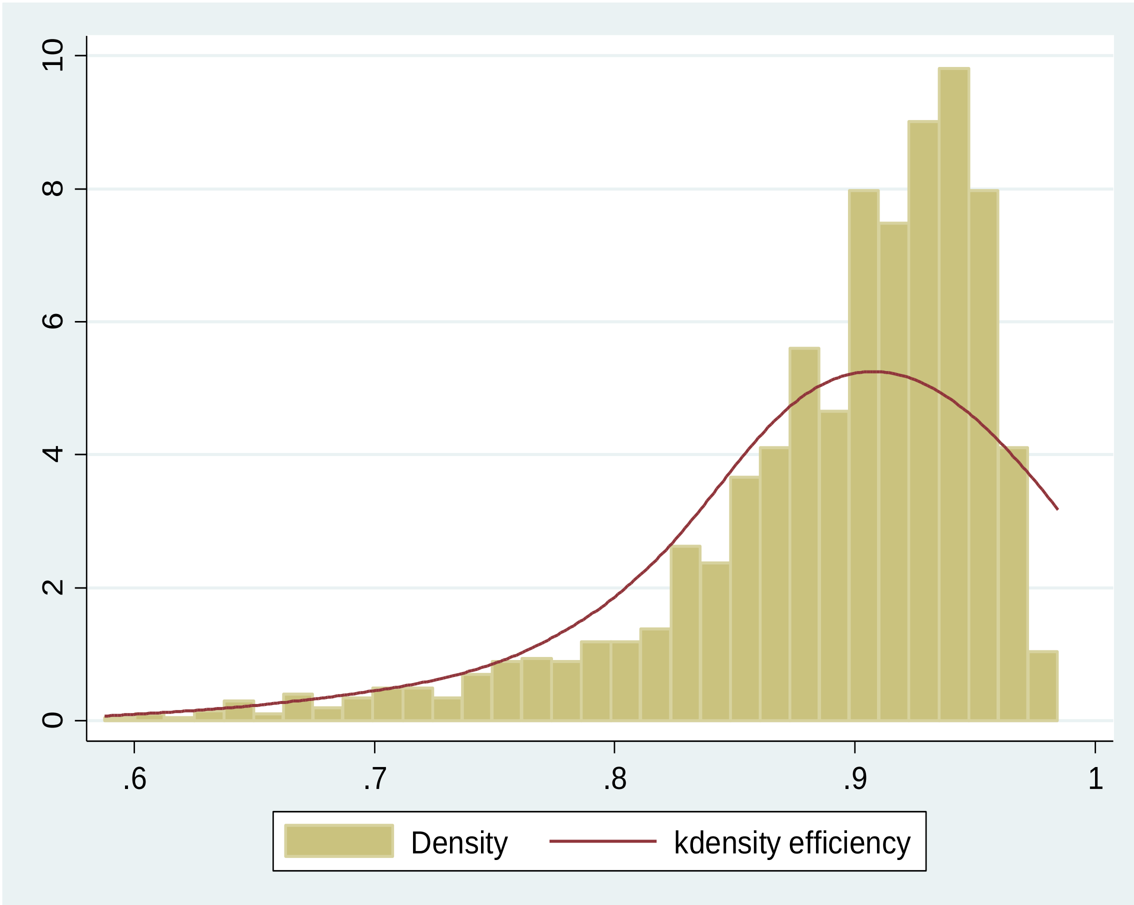

Figure 2. Technical efficiency distribution for those not using direct marketing strategies

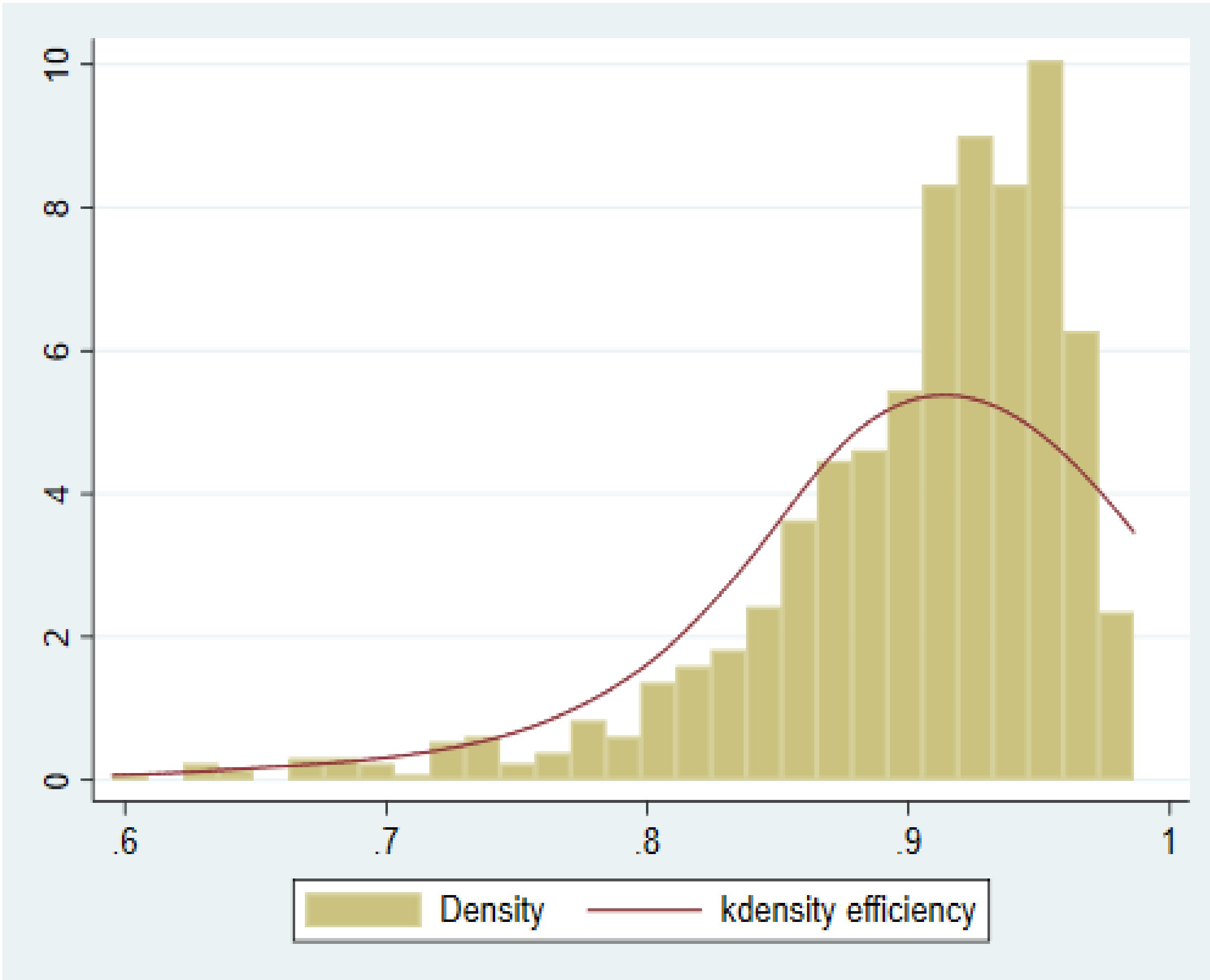

Table 1. Sample Statistics and Variable Summary Statistics

	2015 Sample for U.S. Fruits and Vegetables Growers	
Variable	Mean	Std. Dev.
Total sales (dollars per year)	1,014,644	3,063,594
Land (acres)	606	1,449
Labor (hours per year)	1,624	13,182
Capital (dollars per year)	3,394	49,288
Other inputs (dollars per year)	35.89	17.27
County-level measures		
Average Monthly Max. Temperature (°C)	20.94	5.45
Deviation from 30-year Average (D30) Precipitation for May (mm)	71.30	75.34
D30 Precipitation for June (mm)	92.94	83.45
D30 Precipitation for July (mm)	82.00	77.30
D30 Precipitation for August (mm)	76.10	82.93
D30 Precipitation for September (mm)	72.31	68.66
Mean Temperature for July (°C)	15.17	4.92
Mean Temperature for August (°C)	14.39	5.02
Population density (index)	30,188	18,941
Highway access (max – min meters to ramp)	43,250	51,258
High quality Soil (0 – 100%)	.271	.295
Medium quality Soil (0 – 100%)	.511	.271
Farm household and management characteristics		
Age (years)	60	12
Herfindahl (index)	.105	.175
Production contracts (1,0)	.033	.179
Share of direct sales to total sales (index)	.257	.409
Direct sales (1,0)	.397	.490
Principal operator college education (1,0)	.423	.494
Full-time farmer (1,0)	.777	.416
Number of observations	1,628	

Table 2. Stochastic Frontier Results

	Translog		
	(1)	(2)	(3)
Fruit and vegetable inputs			
Land (*ln x1*)	0.301***	0.271***	0.296***
	(0.0483)	(0.0498)	(0.0518)
Labor (*ln x2*)	0.246***	0.224***	0.194**
	(0.0647)	(0.0660)	(0.0677)
Capital (*ln x3*)	-0.380**	-0.400**	-0.427**
	(0.138)	(0.135)	(0.135)
Other inputs (*ln x4*)	-0.143*	-0.133*	-0.135
	(0.0659)	(0.0678)	(0.0714)
Age	-0.135*	-0.0332	-0.0489
	(0.0526)	(0.0709)	(0.0722)
College	0.0101	0.0164*	0.0151*
	(0.00529)	(0.00685)	(0.00664)
County-level measures			
Average Monthly Max. Temperature	0.245	0.365	0.322
	(0.460)	(0.450)	(0.460)
Deviation from 30-year Average (D30) Precipitation for May	-0.0424	-0.0397	-0.104
	(0.0437)	(0.0433)	(0.0536)
D30 Precipitation for June	0.0562*	0.0541*	0.0438
	(0.0232)	(0.0228)	(0.0233)
D30 Precipitation for July	0.0517	0.0564*	0.0603*
	(0.0266)	(0.0262)	(0.0298)
D30 Precipitation for August	-0.0217	-0.0237	-0.0121
	(0.0223)	(0.0221)	(0.0228)
D30 Precipitation for September	-0.0958***	-0.0961***	-0.0869**
	(0.0231)	(0.0228)	(0.0269)
D30 Mean Temperature for July	-0.204	-0.216	-0.0217
	(0.579)	(0.575)	(0.581)
D30 Mean Temperature for August	0.545	0.517	0.468
	(0.377)	(0.380)	(0.367)
Road Density	0.145	0.132	0.163*
	(0.0795)	(0.0783)	(0.0825)
Highway Access	0.159***	0.170***	0.156***
	(0.0376)	(0.0371)	(0.0382)
High Quality Soil	-0.0481	-0.0444	-0.0388
	(0.0246)	(0.0240)	(0.0248)
Med. Quality Soil	-0.0173	-0.0157	-0.0174
	(0.0182)	(0.0179)	(0.0186)
ln σ_v^2 (Noise)			
	0.0582	0.0573	-

ln σ_u^2 (Inefficiency)			
	0.1499	-	-
Farm household and management characteristics			
Age		1.838	1.782
		(1.090)	(1.162)
Principle operator college education		0.0664	0.0591
		(0.113)	(0.114)
Share of direct sales		0.432***	0.409***
		(0.104)	(0.106)
Herfindahl		-0.219	-0.161
		(0.266)	(0.264)
Full-time farmer		-0.294**	-0.318**
		(0.106)	(0.107)
Production contracts		-1.397***	-1.326**
		(0.406)	(0.431)
Number of observations	1,628	1,628	1,628

Notes: Standard errors in parentheses
*, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively.
For parsimony we do not report regional fixed-effect estimates present in all models nor translog quadratic terms. Model 1 does not include estimates of U or V, corresponding to Equations 9 and 10, respectively. Model 2 does not include estimates of V, while Model 3 includes estimates of both U and V.
The translog terms were: $\mathrm{x}_i^2, i = 1, \ldots, 4$ and $\mathrm{x}_i \mathrm{x}_j, \forall i$ and j where $j = 2,3,4$ and $i < j$.

Table 3. Efficiency differences between direct marketers and wholesale marketers

	Farm size measured by total sales			
	Q1 (*Small*)	Q2 (*Medium*)	Q3 (*Large*)	Total
Direct marketing				
Mean technical efficiency	0.832*	0.907	0.940*	.885*
Standard deviation	(0.082)	(0.043)	(0.033)	(.0767)
Number of observations	274	192	181	647
Wholesale marketing				
Mean technical efficiency	0.850*	0.911	0.928*	.900*
Standard deviation	(0.079)	(0.044)	(0.035)	(.0621)
Number of observations	269	351	361	981

Note: LR test of difference of mean estimates between direct and wholesale marketers, $p<.01$ for all combinations.

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