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A Comparative Efficiency Analysis of Cooperative and Non-cooperative Dairy Manufacturing Firms

Christopher A. Kanter, Brent Hueth, and Brian W. Gould¹

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¹ Christopher A. Kanter is a Ph.D. student in the Department of Agricultural and Applied Economics at the University of Wisconsin-Madison. Contact: ckanter@wisc.edu. Brent Hueth is an Associate Professor in the Department of Agricultural and Applied Economics at the University of Wisconsin-Madison. Contact: hueth@wisc.edu. Brian W. Gould is a Professor in the Department of Agricultural and Applied Economics at the University of Wisconsin-Madison. Contact: bwgould@wisc.edu.

Abstract

Due to differences in ownership structure between cooperative and non-cooperative firms (NCFs), it has been hypothesized that co-ops may be less efficient than their non-cooperative counterparts. Illiquidity of owners' investment and democratic governance may lead to underinvestment and managerial shirking in cooperative firms, both technical inefficiency sources, and the lack of a clear profit motive generates "inefficient" (relative to a profit-maximizing firm) economic decisions. This is especially true in the dairy product manufacturing sector, where production is capital intensive and factors leading to non-optimal investment decisions may have a large impact on efficiency. In this research we will use a unique dataset that includes plant level panel data for dairy product manufacturers from the Census of Manufactures encompassing the years 1977-2007 to determine whether there is a difference in plant level efficiency between cooperative firms and NCFs, as well as the source of any measured inefficiency. We will employ Data Envelopment and Stochastic Frontier (SFA) analyses to ensure robustness of results across alternative methodologies for productivity measurement.

I. Introduction

Cooperative firms are common in agricultural markets throughout the world. In the United States, they handle nearly a third of farm sales and account for a similar fraction of the variable inputs that farmers purchase (USDA, 2004). Some policy makers view farmer cooperatives in a positive light as a response to market power of downstream processors. Under this view, cooperatives promote competition by placing price pressure on intermediaries. They are also seen as providing a set of services to farmers that are not available from non-cooperative firms (NCFs). Others believe that cooperatives are the result of preferential tax treatment and other forms of government support. Their ownership structure is asserted to support inefficiency both at the firm and farm level, and the pressure cooperatives place on prices is seen as anti-competitive behavior rather than as a response to unequal market power.

The cooperative form of business plays an important role in the U.S. economy. Our research will provide empirical evidence on the relative efficiency of cooperative and non-cooperative firms in the dairy processing sector by measuring the efficiency of dairy product manufacturing firms at the plant level, and determining the source of any measured inefficiency. This information is useful for understanding the role of cooperatives in agricultural markets, and more generally for evaluating the effect of ownership structure on firm behavior.

We focus on dairy product manufacturers given the importance cooperatives play in the manufacturing and marketing and dairy product manufacturing. In 2007, 83% of U.S. raw milk was marketed by cooperatives. In terms of manufactured dairy products, the importance of cooperatives varies across commodity: butter - 71% manufactured by cooperatives, dry milk products - 94%, cheese - 26%, packaged fluid milk - 7%, and dry whey - 42% (USDA, 2007).

Arguably, the cooperative form of business organization developed largely as a response to the vulnerability of the many farms to the monopsony power of their few large customer firms. This has especially been the case for DPMs. Historically, raw milk was produced by large numbers of small-sized dairy farms. Dairy product manufacturing, on the other hand, often requires large amounts of capital to reach an efficient scale, resulting in production being concentrated in relatively few firms. The combination of many farmers selling raw milk to a small number of dairy processing firms led farmers to form cooperatives both in the marketing of raw milk and manufacture of dairy products to counterbalance the market power of DPMs.

In contrast to previous analyses of the U.S. dairy manufacturing sector, we will use plant-level data not previously available for productivity analysis (Porter and Scully (1987), Ferrier and Porter (1991), Singh, Coelli, and Fleming (2001)). We have access to the U.S. Census Bureau's Census of Manufacturers over the period 1977-2007. These data provide detailed longitudinal information on inputs and outputs of manufacturing plants and cover the entire population of dairy processors in the United States. Previous work has relied on cross-sectional or incomplete panel data so the data we intend to use will provide substantial opportunity for new insight.

Unlike previous analyses that assume cooperative and non-cooperative firms operate using the same production technology, we allow for within-market specialization. Our data allow us to identify final product codes at the 6-digit NAICS level so that we can identify whether firms operate in the same market space. While previous analyses have generally assumed that cooperative and non-cooperative processors compete with one another in product and input space. The market reality in the U.S. dairy sector is that cooperatives often provide service to non-cooperative processors. For example, cooperatives source and procure milk from farmers,

"balance" dairy supply and demand with large-scale storage capacity, and convert unneeded raw milk into storable butter, cheese, and powder products. In contrast, non-cooperative firms tend to specialize in higher value "soft" products such as yogurt and ice cream. To the extent that cooperative and non-cooperative firms have separate market niches, care must be taken to avoid inappropriate productivity comparisons.

II. Previous Literature

2.1 Dairy Manufacturing Cooperatives and Efficiency

The modern discussion of comparative efficiency in dairy manufacturing was begun by Porter and Scully (1987). By the application of regression techniques they find that cooperative dairy processors are less technically and allocatively efficient. Ferrier and Porter (1991) find a similar result using a Data Envelopment Analysis technique. Sexton and Iskow (1993) criticize these previous studies for the data used in the analysis. For example, Porter and Scully (1987) use a uniform value for wage labor, even though the firms considered in the study are located in widely varying geographic regions, and therefore unlikely that the cost of labor is uniform between these regions. However, some of the issues present in both Porter and Scully (1987) and Ferrier and Porter (1991) occur because of public-use requirements imposed by their use of Manufacturing Census data. In both these analyses the authors aggregate dairy processors into 3-plant units in order to avoid potential plant identification issues. Our direct access to Census microdata will allow for establishment-level (i.e., different plants of the same firm) analysis.

Singh, et al (2001) take the suggestions of Sexton and Iskow (1987) into account, and use careful sample selection and theoretically correct notions of efficiency to analyze dairy processors in India. Using both stochastic frontier analysis (SFA) and Data Envelopment Analysis (DEA) they find that cooperative and NCF dairy processors have very similar levels of

technical and allocative inefficiency, supporting the hypothesis of Sexton and Iskow (1987). The authors make use of a single aggregated measure of dairy product output for each plant rather than explicitly modeling the multi-output nature of dairy processing. We will add to the literature by using methods that allow for both multiple inputs and multiple outputs to estimate firm and time-varying efficiency estimates, as well as using our access to the Census of Manufactures to find more reliable estimates of efficiency.

2.2 Previous Literature: Technical and Allocative Efficiency

There is a large literature on the measurement of allocative and technical efficiency (JEL citation). Much of this literature focuses on estimation of production frontiers. Estimation of a production frontier poses a difficult empirical challenge, as a production frontier represents the “best practice” for a production technique. Thus, standard regression estimates of a production frontier that allow for both positive and negative deviations from the frontier are inappropriate for efficiency analysis. The two main techniques that have developed to address this unique challenge are nonparametric techniques such as DEA, and parametric techniques such as SFA (Emrouznejad, et. al., 2008) . DEA is a linear programming method that uses input and output data to construct a production frontier, with any deviation from the frontier indicating inefficiency. SFA is similar in that input and output data are used to construct a production frontier. The SFA utilizes regression techniques rather than linear programming, and, with SFA, deviations from the production frontier associated with measurement error are modeled separately from deviations due to inefficiency (Kumbhakar and Lovell, 2000).

The genesis of the modern estimation of technical efficiency via frontier techniques is based on the work of Debreu (1951) and Farrell (1957). Nonparametric techniques extended the work of Charnes, et. al. (CCR, 1978). They used the production frontier concepts of Debreu

(1951) and Farrell (1957) and developed DEA as a way of using linear programming to let the data describe the shape of a production frontier (assuming constant returns to scale). In contrast, CCR (1978) measure efficiency as a proportional decrease in input used to produce a given output or a proportional increase in output possible with a given set of inputs.

Subsequent work in nonparametric techniques largely built off of the initial work by CCR (1978). Banker et al. (1984) developed a method to allow for variable returns to scale. Charnes et al. (1985), Tone (2001), and Green et al. (1997) created non-radial DEA methods that allow for non-proportional adjustments in inputs or outputs to more fully capture the nature of production. For example, achieving technical efficiency may involve a large decrease in the use of one input and a small decrease in the use of another; non-radial efficiency measures capture this type of inefficiency while radial measures will not. Fare and Grosskopf (1996) led the way in creating multi-level models that can measure technical efficiency in production methods that involve production by several different decision making units (DMU), such as a firm making a decision to allocate production between multiple plants. Banker and Morey (1986) developed a model that allows for inclusion of categorical variables as inputs, while Cook et al. (1993, 1996) developed models that allow for inclusion of ordinal variables.

The parametric efficiency literature takes a different approach to modeling technical efficiency. The SFA literature also takes the work of Debreu and Farrell as its starting point. Aigner et al. (1977) and Meeusen and van den Broeck (1977) developed the principle that, instead of DEA, where we put no structure on the relationship between inputs and outputs, we could instead model the input-output relationship parametrically using a production function. Both sets of authors acknowledged that error in the econometric estimation could come either from random sources (measurement error, equipment failure, weather shocks), or from

mismanagement. This latter error type is the measure of technical inefficiency. Because the production frontier in SFA represents a “best practices” frontier, the technical efficiency error term is one-sided (i.e. it takes only negative values), and a value other than zero for the error term indicates inefficiency.

Much of the early research in SFA focused on alternate formulations for the technical efficiency error term in regressions. Aigner et al. (1977) and Meeusen and van den Broeck (1977) both impose a half-normal distribution on the one-sided error term. Stevenson (1980) imposed a truncated normal distribution on the one-sided error term, while Greene (1980 a,b) and Stevenson (1980) assumed a gamma distributed error term. Coelli and Perelman (1996), Fuentes, et. al (2001), Morrison and Johnston (2000) and Reinhard and Thijssen (1998) advanced the SFA literature by developing models using distance functions, which unlike earlier models, allow for both multiple inputs and multiple outputs. Horrace and Schmidt (1996, 2000), Kumbhakar (1987), and Battese and Coelli (1988) extended SFA to allow for the use of panel data, and Cornwell, et.al. (1990), Lee and Schmidt (1993), and Khumbhakar (1990) and Battese and Coelli (1992) further extended SFA to allow for technical efficiency to be time-varying. The work of Paul and Nehring (2005) synthesizes the above to create a firm and time-varying model of technical efficiency that allows for the use of multiple inputs and outputs through the use of distance functions.

The SFA methods described above have the weakness of sensitivity to the specification of the error term. That is, the specification is chosen by the researcher, and is not necessarily implied by economic theory. The *shadow price* approach, first described by Hopper (1965), and further developed by Lau and Yotopolous (1971), addresses this weakness by parameterizing inefficiency rather than treating it as a residual. Producers may fail to maximize profits given

observed prices, but they are assumed to maximize profits with respect to shadow prices, where the shadow price is constructed by multiplying the observed price by a scale factor. The shadow price approach assumes that firms equate the marginal product of an input and the real shadow price of the input. This can be contrasted with traditional economic theory, where firms are assumed to equate the marginal product of an input and the real observed price of the input. By scaling observed prices and replacing them with shadow prices during estimation, it is possible to test whether shadow prices diverge from observed prices by testing whether the scale factor deviates from a value of 1. This divergence represents allocative inefficiency. Lau and Yotopolous (1971) demonstrate use of the shadow price method using a single-output, Cobb-Douglas profit function and cross-sectional data. Atkinson and Halvorsen (1980) and Kumbhakar (1996) further develop the technique by allowing for flexible functional forms and multiple outputs for the profit function. This is the approach we will follow in our project.

2.3 Theoretical Impacts of Cooperative Ownership on Efficiency

As noted above, recent concerns centered on dairy cooperative efficiency were sparked by Porter and Scully (1987), and continued by Ferrier and Porter (1991). The issue of cooperative efficiency focuses on three problems associated with the cooperative business form: horizon, transferability, and control (Sexton and Iskow 1993). The control problem is an issue that has the potential to be present for a cooperative in any sector; the horizon and non-transferability issues, however, are far more likely to be present for cooperative firms in sectors that rely on large amounts of capital.

The horizon problem arises because cooperative owners' claim on net cash flow is often shorter than asset life. For cooperatives, returns to equity holders are limited by law to 8% per year (Zeuli and Cropp 2012). For this reason a large portion of profit is returned through

patronage refunds that are proportional to the member's sales to the cooperative rather than dividend payments, which are based on the amount of equity held by a member. This implies a member's ability to earn a return on an investment made by the cooperative ends when the patronage relationship ends. This implies that cooperative members will prefer shorter-term investment they believe will pay off during the time they plan to patronize the cooperative when compared to their non-cooperative counterparts. This is an especially important issue in capital intensive DPMs that are reliant on long-term investment to capture scale and other efficiencies.

The cooperative non-transferability problem arises because of the nature of firm ownership. Cooperatives are owned by their patrons (both past and present). Original cooperative members are required to provide capital when the cooperative is founded. The cooperative may retain earnings to pay for investments. Cooperative members may receive equity in the firm in return for their capital, though this is not always the case. However, equity in a cooperative firm is different than equity in a non-cooperative firm (NCF). Cooperative equity holders may not trade their shares in the cooperative firm with other members or non-members. The only option for those who own equity in a cooperative firm for selling their equity is to sell shares back to the cooperative at par value. That is, if the share cost the member \$100 in 1980, they would receive \$100 in return if they sold the share back to the cooperative in 2013.

Additionally, the exchange of shares between equity holders and the firm is enacted at the firm's discretion; an equity holder cannot force a cooperative to buy back their shares. Interest payments on the equity shares are allowable at market rates, but the actual transfer of equity shares must occur at the constant nominal value. These buy backs often occur in a revolving equity arrangement, where cooperatives retire the oldest equity shares first while at the same

time issuing new shares to current patrons. This unique form of equity holding means that, unlike traditional NCFs, owners of equity in a cooperative cannot capitalize the value of future earnings into the value of their equity and cannot buy or sell shares according to their risk preferences. Because cooperatives are run by their members, this in turn means that members may be hesitant to provide additional equity to the firm. This can result in underinvestment when compared to NCFs.

The biggest issue often cited when examining cooperative firms is the control problem. The control problem generally refers to the issues that cooperative owners (patrons) have in monitoring the activities of their managers. NCFs have a natural monitoring mechanism in the form of equity markets. These markets analyze both present and expected performance of a firm and provide equity holders an assessment of manager ability. Cooperatives do not have such a mechanism. Holders of cooperative equity must rely on their own financial information and judgment of manager performance to determine whether managers are performing adequately. The extra costs needed to measure manager performance imply that it is more likely that inefficiencies exist in the production process.

It is not clear that the factors inducing the control problem have a purely negative influence on efficiency. For instance, while lack of secondary markets for equity may increase the cost of monitoring management, there are other factors that may decrease the costs of monitoring for cooperative firms compared to NCFs. Since cooperatives are run by their members, who may have large amounts of experience in their industry, it may be that monitoring is less costly for cooperatives than for NCFs. Cooperatives may be less reliant upon the information provided by secondary equity markets to judge the performance of management than NCFs. Therefore, while it is fairly clear that, if present, the non-transferability and horizon

problems would reduce efficiency for cooperative firms, it is not clear that the control problem would have a net negative effect on cooperative efficiency.

III. Measuring Efficiency

In the previous sections we have outlined issues that give rise to concerns that cooperative firms are inefficient compared to non-cooperative firms. These issues lead us to pursue the primary objective of determining whether cooperative ownership has any impact on plant level productivity, as well as determining the specific sources of inefficiency.

In order to achieve our objectives we intend to use a two-step approach to measure productivity in the manufacturing of a variety of dairy products. In the first step, we will estimate time and plant-varying technical and allocative efficiency measures using nonlinear systems econometric estimation procedures applied to multi-input, multi-output profit and profit share functions. We will use both DEA and SFA techniques to ensure the robustness of our results. In the second step, we will examine the relationship between first step efficiency estimates on exogenous environmental variables (including ownership structure) to identify the role cooperative ownership has on these efficiency measures. This two-step approach is preferable to estimating the efficiency of cooperative and non-cooperative firms separately because it allows us to control for multiple factors that may impact efficiency simultaneously. We will also use bootstrapping techniques suggested by Simar and Wilson (2007) to correct for bias in the technical efficiency estimates.

This section proceeds as follows. First we will review the economic theory underlying efficiency measurement. We will then outline the first-step DEA and SFA procedures that will be used to estimate technical and allocative efficiency, as well as the second-step procedure in which we will measure the impact of cooperative ownership on technical efficiency. Lastly, we

will describe the procedure suggested by Simar and Wilson (2007) that we will use to correct for bias in our technical efficiency estimates.

3.1 How Can We Measure Efficiencies in Dairy Product

Manufacturing?

In the following section we will describe the efficiency measures that will be used to evaluate whether inefficiency is indeed greater in cooperative DPMs than those that are NCFs. Consider a firm making use of an vector of M inputs, $X = (X_1, \dots, X_M)$ to produce N outputs, $y = (y_1, \dots, y_N)$. The production possibility set can be represented as $F_V(y, -X)$ which characterizes the feasible set of outputs that can be produced given the underlying technology and resource endowment.

We can define a cost function that shows the relationship between the lowest cost of producing a given level of output, y , using inputs x with input prices, r . Given $r = (r_1, \dots, r_M)'$, the vector of input prices for input vector X , the cost function is given as the solution to the following minimization problem:

$$C(r, y) = r'X^* = \min_x \{r'x \text{ such that } (y, -X) \text{ is feasible}\} \quad (1)$$

with X^* being the cost minimizing input demand function under a given technology.

With our characterization of the underlying technology F , we can adopt a measure of technical efficiency that was first developed by Farrell(1957). This technical efficiency index, TE, can be represented as:

$$TE(y, X) = \min_k \{k \text{ such that } (y, -kX) \text{ is feasible, for } k \geq 0\} \quad (2)$$

The index TE represents the minimum proportion, k , by which X can be decreased while still producing a particular level of output k can be considered a measure of wasted input; in the presence of technical inefficiency, fewer inputs could have been used to produce the same level of output. If production is technically efficient, $k=1$, indicating that input use could not be scaled

down while producing the same level of output. If production is technically inefficient, $0 < k < 1$, indicating input use could be scaled down while producing the same level of output. Given the above relationship between the scale factor k and technical efficiency, the index TE will take on values between 0 and 1. Firms producing on the production frontier have a TE value of 1. $(1 - TE)$ is the largest proportional decrease in inputs that can be achieved while still producing output y .

In the context of our study, a departure from a TE value of 1 indicates that a firm is not effectively using its technology and opportunities to proportionately decrease input use and reducing cost while maintaining the level of output exist. Note that this measure of technical efficiency is a physical relationship not dependent on either output or input prices.

In contrast to the measure of technical efficiency we can define a measure of allocative efficiency that not only incorporates characteristics of the production function but also accounts for input costs. Allocative efficiency is a measure of how close technically efficient firms (i.e., the subset of firms on the technically efficient frontier) are to using the *least cost input mix* to produce a given production level. The Farrell(1957) allocative efficiency index for a given input mix x can be represented as:

$$AE(r,y,F_v) = C(r,y,F_v) / [r'X_{TE}] \quad (3)$$

where X_{TE} is a technically efficient input vector identified via equation (2) (Chavas and Aliber, 1993). $C(r,y,F_v)$ gives the lowest cost of producing output level y , as described in equation (1). $r'X_{TE}$ gives the cost of using inputs X_{TE} to produce the same level of output y ; however, the output is not necessarily produced using the same mix of cost minimizing inputs. As a result, $r'X_{TE} \geq C(r,y,F_v)$, implying that AE takes a value between 0 and 1. An AE index of 1 indicates that the firm is engaging in cost-minimizing behavior. An AE of < 1 is indicative of a firm that is

not producing at minimum cost. $(1-AE)$ represents the largest cost proportion a technically efficient firm can save by using the cost minimizing input levels. In the context of this study, a departure from an AE value of 1 can represent mismanagement within the firm, as the least cost input mix is not being used to produce a given level of output. Given TE and AE, we can create a measure of overall economic efficiency ($AE*TE$), with $(1-AE*TE)$ representing the largest percentage costs that can be decreased by the firm becoming both technically and allocatively efficient.

3.2 Empirical Implementation

There are two methods that may be used in the first step to calculate efficiency estimates; a parametric approach and a nonparametric approach. The parametric approach typically involves the assumption of a specific functional form for a production, cost, or profit function. Each function has associated parameters that describe a relationship between the input and output variables. The parametric approach is used to estimate these parameters using regression analysis. However, the parametric approach has the weakness of imposing restrictions on model parameters in order to satisfy economic theory. Parametric approaches have been more common for analyzing the economic efficiency of multi-input, single-output production and less common for analyzing multi-input, multi-output production technology, which is prevalent in dairy processing (Chavas and Aliber 1993). This difference in usage is largely due to the large increase in parameters that must be estimated as the number of outputs increases, which can be problematic for estimation using small samples. Recently developed techniques make this less of a problem; parametric methods using production functions, cost functions, and profit functions are now available that allow one to accommodate the multi-input, multi-output nature of dairy processing while requiring the estimation of a feasible number of parameters. The

shadow price approach is a parametric SFA approach that is effective for estimating technical and allocative efficiency with multiple inputs and outputs. The shadow price approach models allocative inefficiency directly as parameters in the model, rather than more traditional production, cost, and profit function frontier approaches in which allocative inefficiency is either ignored or modeled as a component of the error term, while still modeling technical efficiency as a component of the error term.

Alternatively, the nonparametric approach is well-suited to investigating efficiency issues within a multi-output context. It is not necessary to make assumptions regarding the underlying production technology. The evaluation of technical efficiency is straightforward using nonparametric methods such as Data Envelopment Analysis (DEA), a linear programming method that can be used to measure the efficiency of observations relative to the production frontier. One of the major difficulties with using DEA for efficiency analysis is performing hypothesis testing on the results can be complicated since we make few distributional assumptions regarding the data generating process. Furthermore, when using DEA, there is no distinction between measurement error and inefficiency (i.e. all deviation from the frontier is interpreted as inefficiency).

Because parametric and nonparametric methods each have their strengths and weaknesses, we will use both approaches in our efficiency estimates to ensure that any impact of cooperative ownership found is not a result of the method used. In the following sections we will first outline the DEA approach, and then outline the shadow price SFA approach.

3.3 Estimating technical and allocative efficiency using the DEA approach

An investigation of milk processing efficiency using DEA can be implemented using equations that build off of the theoretical concepts of efficiency and cost presented in section 3.1. Suppose we have n observations on firms in a competitive milk processing industry, with x^{it} and y^{it} being the input and output vectors of the i^{th} firm, $i=1,\dots,I$. Then a nonparametric representation of the production possibilities set for each firm in the industry can be given as:

$$F = \left\{ (y, -x) : y \leq \sum_{i=1}^I \lambda_{ii} y^{ii}, x \geq \sum_{i=1}^I \lambda_{ii} x^{ii}, \sum_{i=1}^I \lambda_{ii} = 1 \right\} \quad (4)$$

This is the smallest convex set that includes all of the firm observations. Thus, since all of the observations represent actual allocations, F_V can be considered an inner bound on the firms' actual production possibilities set.

Given this representation of F_V , the technical efficiency index for the i^{th} firm from equation (2) can be found as the solution to the linear programming problem:

$$TE(y^i, x^i, F) = \min_{k, \lambda} \left\{ k_{ii} : y^{it} \leq \sum_{j=1}^I \lambda_{ji} y^{jt}, k_{ii} x^{it} \geq \sum_{j=1}^I \lambda_{ji} x^{jt}, \sum_{j=1}^I \lambda_{ji} = 1 \right\} \quad (5)$$

Then let r be the vector of prices for inputs x . Using (4), and the following characterization of the cost function found by solving (6) via linear programming, the allocative efficiency index AE for the i^{th} firm can be found using equation (3):

$$C(r, y^i, F) = \min_{x, \lambda} \left\{ r'x : y^{it} \leq \sum_{j=1}^I \lambda_{ji} y^{jt}, k_{ii} x \geq \sum_{j=1}^I \lambda_{ji} x^{jt}, \sum_{j=1}^I \lambda_{ji} = 1 \right\} \quad (6)$$

3.4 Estimating technical and allocative efficiency using the shadow price SFA approach

Following the approach of Kumbhakar (1996), a parametric investigation of milk processing efficiency can be implemented via the following. Consider firm i ($i = 1, \dots, I$) at time t ($t = 1, \dots, T$) making use of an vector of M inputs, $X=(X_1, \dots, X_M)$ to produce N outputs, $Y=(y_1, \dots, y_N)$. Then we can define a multi-input, multi-output observed normalized profit function (with the profit function normalized by output price p_1) for firm i at time t as:

$$\begin{aligned} \left(\frac{\pi}{p_1} \right)_{it} &= y_{1it} + \sum_{n>1} \left(\frac{p_{nit}}{p_{1it}} \right) y_{nit} - \sum_n \left(\frac{w_{mit}}{p_{1it}} \right) x_{mit} \\ &= \phi_{it} \cdot \pi[(p, w)_{it}^*] \cdot \left\{ 1 + \sum_n \left(\frac{1 - \kappa_{ni}}{\kappa_{ni}} \right) R_{nit}^* + \sum_m \left(\frac{1 - \theta_{mi}}{\theta_{mi}} \right) S_{mit}^* \right\} \end{aligned} \quad (7)$$

where p_{nit} , is the price for output n ($n = 2, \dots, N$), w_{mit} , is the price for input m ($m=1, \dots, M$), and $(p, w)_{it}^* = [\kappa_{ni}(p_{nit}/p_{1it}), (\theta_{mit}/\phi_{it})(w_{mit}/p_{1it})]$ is a normalized shadow price vector accounting for both technical inefficiency (ϕ) and allocative inefficiency ($\kappa_n, n=2, \dots, N, \theta_m, m=1, \dots, M$), and $\pi[(p, w)^*]$ is the shadow profit function, indicating the level of profit assuming the firm is optimizing production by equating input marginal product and real normalized shadow prices $(p, w)_{it}^*$. $0 \leq \phi \leq 1$ is the technical efficiency parameter. The shadow profit function assumes that production is technically efficient; ϕ accounts for potential technical inefficiency and scales profits down accordingly, with $\phi=1$ indicating technical efficiency and $0 < \phi < 1$ indicating some technical inefficiency. κ and θ are the shadow price scale factors. These factors indicate whether the shadow input and output prices firms are assumed to use for their profit maximization decision deviate from observed prices. $\kappa, \theta=1$ indicates firms are profit maximizing with respect to actual, observed prices (i.e. shadow prices and observed prices are

equal), and therefore the firms are allocatively efficient. $\kappa, \theta \neq 1$ indicates that shadow prices deviate from observed prices, and therefore firms are allocatively inefficient.

$$\begin{aligned} R_{nit}^* &= \frac{P_{nit} y_{nit}}{\pi[(p, w)_{it}^*]}, n = 2, \dots, N, i = 1, \dots, I, t = 1, \dots, T \\ S_{mit}^* &= \frac{w_{mit} x_{mit}}{\pi[(p, w)_{it}^*]}, m = 1, \dots, M, i = 1, \dots, I, t = 1, \dots, T \end{aligned} \quad (8)$$

are the shadow output and input profit shares (that is, the percent of profits represented by revenue from a given input, or cost of a given output) respectively. Given these equations, we can also note the relationship between observed normalized profit and shadow normalized profit

$\pi[(p, w)^*; \beta]$:

$$\left(\ln \frac{\pi}{P_1} \right)_{it} = \ln \pi[(p, w)_{it}^*; \beta] + \ln H_{it} + \ln \phi_{it}$$

where

$$H_{it} = \left\{ 1 + \sum_n \left(\frac{1 - \kappa_{ni}}{\kappa_{ni}} \right) R_{nit}^* + \sum_m \left(\frac{1 - \theta_{mi}}{\theta_{mi}} \right) S_{mit}^* \right\}$$

The relationship between observed profit shares R_n and S_n and shadow profit shares is:

$$\begin{aligned} R_{nit} &= \frac{P_{nit} y_{nit}}{\pi_{it}} = \frac{1}{H_{it}} \cdot \frac{1}{\kappa_{ni}} R_{nit}^*, n = 2, \dots, N, i = 1, \dots, I, t = 1, \dots, T \\ S_{mit} &= \frac{w_{mit} x_{mit}}{\pi_{it}} = \frac{1}{H_{it}} \cdot \frac{1}{\theta_{mi}} S_{mit}^*, m = 1, \dots, M, i = 1, \dots, I, t = 1, \dots, T \end{aligned} \quad (10)$$

We now need to parameterize our model by assuming a functional form for our profit function.

With a translog profit function, our normalized shadow profit function can be written as:

$$\begin{aligned} \ln \pi[(p, w)_{it}^*; \beta] &= \beta_0 + \sum_n \beta_n \ln p_{nit}^* + \sum_m \gamma_m w_{mit}^* + \frac{1}{2} \sum_j \sum_n \beta_{jn} \ln p_{jit}^* \ln p_{nit}^* \\ &+ \frac{1}{2} \sum_k \sum_m \gamma_{km} \ln w_{kit}^* \ln w_{mit}^* + \sum_m \sum_n \delta_{mn} \ln w_{mit}^* \ln p_{nit}^* \end{aligned} \quad (11)$$

with the β 's describing the relationship between input and output shadow prices and firm profit.

The shadow profit shares obtained using the translog profit function are:

$$\begin{aligned} R_{nit}^* &= \beta_n + \sum_j \beta_{jn} \ln p_{jit}^* + \sum_m \delta_{mn} \ln w_{mit}^*, n = 2, \dots, N, i = 1, \dots, I, t = 1, \dots, T \\ S_{mit}^* &= \beta_m + \sum_k \gamma_{km} \ln w_{kit}^* + \sum_n \delta_{mn} \ln p_{nit}^*, m = 1, \dots, M, i = 1, \dots, I, t = 1, \dots, T \end{aligned} \quad (12)$$

We then substitute the parameterized shadow profit and shadow input and output profit share equations (11) and (12) into equations (9) and (10). After substitution this yields a system of $M+N$ equations. Assuming $\ln \phi_{it}$ is distributed multivariate $N^+(0, \sigma_\phi^2)$ (this is the one-sided technical efficiency error term), and adding a random error vector v_{it} distributed multivariate $N(0, \sigma_v^2)$, we may estimate the system of equations using a nonlinear ITSUR regression method.

3.5 Measuring the impact of cooperative ownership on technical efficiency

The previous sections describe two methods that will be used to estimate a set of technical efficiency parameters for firm i at time t , ϕ_{it} , and a set of allocative efficiency parameters κ_{it} and θ_{it} . We can now describe the second step econometric estimation, in which we regress efficiency estimates on non-input exogenous variables, with particular emphasis on the impact of a variable indicating cooperative firm ownership. We consider only the technical efficiency estimates from the first step estimates in the second step analysis. The allocative efficiency estimates from the first step in the SFA approach indicate whether a firm is cost-minimizing for a given level of output; they are not strictly a measure of efficiency as described in section 3.1.

While it is possible to perform a second step regression of the type described below on the

allocative efficiency measures, such an analysis would be ad hoc in nature, and the results must be interpreted with care.

The second step proceeds as follows. In the second step we use the estimated technical efficiency measures obtained from the first step as a dependent variable in the following general regression equations:

$$\phi_{it} = f(Z_{it} | \beta) + \varepsilon_{it}$$

where ϕ_{it} are our first step estimates of technical efficiency for firm i at time t , Z_{it} is a vector of environmental variables and ε_{it} is an error term distributed $N(0, \sigma^2_{\varepsilon})$

This two-step approach is preferable to estimating the efficiency of cooperative and NCFs separately because it allows us to control for multiple factors that may impact efficiency simultaneously (Simar and Wilson 2007). In our second step estimation we will incorporate categorical variables that identify alternative forms of ownership. These variables will allow us to test hypotheses concerning the marginal effect of cooperative ownership on our efficiency measure. Given our second-step estimation equation, testing the hypothesis that cooperative DPMs are less efficient than NCFs is straightforward by evaluating whether the marginal effects of these variables are statistically significantly different from zero.

There are complications with the two-step approach. The efficiency estimates used as the dependent variable in the second step are serially correlated (Simar and Wilson, 2007).

Therefore any slight change in frontier observations affects all estimated efficiencies and biases the estimates in finite samples. This leads to any inference about coefficients that are calculated without taking account of this correlation being unreliable. Simar and Wilson (2007) describe a bootstrapping technique that corrects this serial correlation, making inference based on the second step possible. By performing this bootstrapping procedure we have greater confidence

that any impact of cooperative ownership on efficiency that is detected in the second-step regression is the result of actual efficiency differences between cooperatives and NCFs, and not a result of econometric misspecification.

Additionally, SFA analyses are extremely sensitive to the quality of the data used. As noted above we will make use of our access to the Census of Manufactures and the Annual Survey of Manufacturers to obtain more detailed data related to cost, input use and type of business form than is typically available for efficiency analysis. Thus our efficiency estimates will be less subject to the problems posed by questionable data quality. In addition to a high level of data quality, we have the ability to follow the performance of a particular firm over the period 1977–2007, which will enable us to track whether the relative efficiency of cooperatives is changing over time.

IV. Results and Conclusion

Forthcoming

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