Technical efficiency and spatial spillovers: Evidence from grain marketing cooperatives in the US Midwest

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Abstract
To date, no study has investigated the role of spatial spillovers in the technical efficiency of farmer cooperatives. This study addresses this issue by employing a two-stage approach, first measuring cooperatives’ technical efficiency using a Data Envelopment Analysis (DEA) model and secondly using a bootstrap truncated regression to identify the effect of spatial spillovers and cooperative firm-level characteristics on technical efficiency. The empirical application focuses on grain marketing cooperatives in the Midwest region of the United States, and shows that spatial spillover effects influence the technical efficiency of neighboring cooperatives. Technical efficiency is also found to be influenced by several cooperative firm-level characteristics including age, liquidity, differentiation, and membership size. [EconLit citations C21, Q13, R3].

KEYWORDS
bootstrap approach, data envelopment analysis, farmer cooperatives, spatial spillovers, technical efficiency

1 | INTRODUCTION

There exist many studies of technical efficiency in the farmer cooperative sector (Ariyaratne, Featherstone, Langemeier, & Barton, 2000; Caputo & Lynch, 1993; Ferrier & Porter, 1991; Guzmán & Arcas, 2008; Huang, Fu, Liang, Song, & Xu, 2013; Kebede & Schreiner, 1996; Krasachat & Chimkul, 2009; Maietta & Sena, 2010; Mosheim, 2002; Piesse, Doyer, Thirtle, & Vink, 2005; Singh, Coelli, & Fleming, 2001; Soboh, OudeLansink, & VanDijk, 2012;...
Sueyoshi, 1999). Past studies have contributed significantly to the understanding of (a) how large technical efficiency is, (b) how technical efficiency varies among individual cooperatives, (c) what are the determining factors that explain variation in technical efficiency, and (d) the comparative efficiency of cooperatives and non-cooperatives. These studies generated useful implications for cooperative managers, external stakeholders, and policymakers interested in improving cooperatives' performance.

However, a topic that has not been investigated in the prior literature is the role of spatial dependence or spatial spillover effects in the technical efficiency of farmer cooperatives. Spatial dependence is defined as the likelihood that units near each other in geographic space are more likely to be related than those further apart (Tobler, 1970). As a result, nearby units (in our case cooperatives) may exhibit interdependent decision-making processes that affect their management practices and, as a consequence, their technical efficiency.

In the case of cooperatives, these interdependencies may arise from four distinct channels. The first channel relates to spatial competition for buyers of outputs. Many buyers at the downstream stage of the agri-food value chain (e.g., Cargill, General Mills) are relatively large and likely have an advantage in bargaining power (Saitone & Sexton, 2017). Many cooperatives thus compete and may face difficulties in marketing all the supplies of their members, leading to decreased output efficiency relative to nearby competitors. The second channel relates to spatial competition for suppliers of inputs when the geographic size of the market in which cooperatives operate is local or regional (Fackler & Goodwin, 2001). Spatial dependence in the pricing strategies of input procurers is evident in, for example, the dairy sector (Alvarez, Fidalgo, Sexton, & Zhang, 2000) and the grain sector (Grashuis, 2019). Spatial price competition to secure supplies from nearby producers may negatively impact the efficiency of nearby competitors, especially if cooperatives force improvements in the input prices offered to farm producers.

The third channel relates to spatial knowledge spillover effects, which may arise through active collaboration or passive observation of geographically proximate peer cooperatives. For example, in relation to Italian wine producers, Vidoli, Cardillo, Fusco, and Canello (2016) found a positive impact of nearby competitors on efficiency and interpreted the result as a network effect: local learning facilitates the diffusion of tacit knowledge among local competitors. Spatial competitors may exhibit herd behavior by making adaptations in response to the collective behavior of the reference group (Maté-Sánchez-Val, López-Hernandez, & Mur-Lacambra, 2017). Such behavior is also expected of cooperatives, for which intra-cooperative cooperation is one of the traditional values and principles. Cooperation may manifest itself by the sharing of information or other resources. Shared knowledge may, for instance, help cooperatives overcome the various barriers to enter new markets (Burress, Cook, & Klein, 2008), thus facilitating an increase in their sales and, as a result, their output efficiency. The fourth channel relates to the so-called “reputation spillover” effect. For instance, a reputational crisis experienced by one cooperative (e.g., a product failure) may spillover to nearby cooperatives and affect negatively their ability to market products. As Yu and Lester (2008) argue, many stakeholders tend to stereotype organizations on the basis of their proximity and relatedness to the organization hurt by a reputational crisis. On the other hand, a positive reputation spillover effect may occur if nearby cooperatives gain a favorable reputation in the marketplace. In a best-case scenario, such a reputation spillover effect is captured and institutionalized by some type of label or scheme (e.g., Bordeaux wine, Gouda cheese, Parma ham). All these factors could lead to spatial spillovers that impact neighboring cooperatives’ technical efficiency and, since technical efficiency indicators are useful in informing decision-making, the value of testing for evidence of spatial spillovers in cooperatives’ technical efficiency is obvious.

A considerable number of studies have investigated the role of spatial spillovers in the technical efficiency of neighboring decision-making units (i.e., farms, regions, or countries), with all studies using stochastic frontier modeling. Some studies have developed stochastic frontier models that account for spatial interaction via the spatial lags of the endogenous and/or exogenous variables or via the spatial autocorrelated error term, all of which shift the production frontier (Adetutu, Glass, Kenjegalieva, & Sickles, 2015; Druska & Horrace, 2004; Glass, Kenjegalieva, & Sickles, 2016). Other stochastic frontier studies have accounted for spatial dependence by specifying the inefficiency to (a) be spatially autoregressive (Areal, Balcombe, & Tiffin, 2012; Fusco & Vidoli, 2013; Pede, Areal, Singbo, McKinley, & Kajisa, 2018; Tsionas & Michaelides, 2016; Vidoli et al., 2016), or (b) be dependent
on a variable that captures unobserved spatial effects (Schmidt, Moreira, Helfand, & Fonseca, 2009). All these studies find evidence of spatial spillovers in the technical efficiency of nearby units.

In this context, the objective of this article is to empirically analyze the role of spatial spillover effects in cooperatives’ technical efficiency. The empirical application, which focuses on 368 grain marketing cooperatives in the Midwest region of the United States, employs a two-step approach: First using a data envelopment analysis (DEA) model to measure cooperatives’ technical efficiency, then employing a bootstrap truncated regression to identify the effect of spatial spillover effects and cooperative firm-level characteristics on efficiency.

This study makes three important contributions to the literature. Two contributions are directed to the literature on the technical efficiency of farmer cooperatives, while one is directed to the literature on spatial dependence in the technical efficiency of neighboring decision-making units. First, we are the first to account and test for the role of spatial spillovers in the technical efficiency of geographically proximate cooperatives. Second, we contribute to the scant literature on the efficiency analysis of US grain marketing cooperatives (Ariyaratne et al., 2000). Third, we present a way to assess the role of spatial spillovers in the technical efficiency of cooperatives using a two-step approach (as described above and later in section 2). The stochastic frontier studies discussed above investigated the role of spatial spillovers in the technical efficiency of nearby units, but they did so using a one-step procedure.

The rest of the article is organized as follows. Section 2 describes the methods used to measure cooperatives’ technical efficiency and assess the determinants of efficiency. Section 3 presents the data and Section 4 the empirical results. Finally, Section 5 contains concluding remarks.

## 2 | METHODOLOGY

### 2.1 | Modeling technical efficiency of grain cooperatives

Assume that there are $I$ grain marketing cooperatives (with $i = 1, \ldots, I$) that produce a single output, $y \in \mathbb{R}$, using a vector of inputs $x = (x_1, \ldots, x_v) \in \mathbb{R}_+^v$. The production technology of these cooperatives can be mathematically characterized by technology set $T$ defined in general terms as

$$ T = \{(x, y): x \text{ can produce } y\}. \quad (1) $$

$T$ is the set of all feasible input-output combinations and it is assumed to be closed and bounded. It is to be noted that many, if not all, of the inputs that grain marketing cooperatives use can be considered as fixed in the short run. For instance, most grain marketing cooperatives have an open membership policy and must, therefore, accept all supplies (i.e., raw materials). Moreover, changes in fixed assets (e.g., property and equipment) are costly and take time to complete. Therefore, a convenient tool for characterizing the production technology $T$ and, in particular, for measuring grain cooperatives’ efficiency is the Farrell/Debreu-type output-oriented technical (in) efficiency measure. This measure for a single grain cooperative is defined as follows:

$$ \text{TE}(x_i, y_i) = \sup_{\delta} \{ \delta : (x_i, \delta y_i) \in T \}. \quad (2) $$

The optimal $TE$ is achieved by maximizing the output level while maintaining the current input level. In practice, the true $T$ is unobserved and it is usually replaced with its DEA estimate, $\hat{T}$, obtained through the following activity analysis:

$$ \hat{T} = \{(x, y): \sum_{i=1}^I \lambda_i y_i \geq y, \sum_{i=1}^I \lambda_i x_i^v \leq x_i^v, v = 1, \ldots, V, \sum_{i=1}^I \lambda_i = 1\}. \quad (3) $$
where \( \lambda_i \geq 0 \) are intensity variables, and the equality expression in (3) allows for variable returns to scale. \( \lambda_i \) and \( \theta \) are jointly optimized in (2) for a given sample of input-output allocations of grain cooperatives.

Note that the true \( T_E \) scores from the Farrell/Debreu measure are bounded between 1 and \( \infty \). Efficient cooperatives have a score of 1 and inefficient ones have a score greater than 1. Meanwhile, the reciprocal of (2) yields the percentage technical efficiency level (between 0 and 1) relative to the estimated best-practice technology frontier.

2.2 | Investigating the role of spatial spillovers on grain marketing cooperatives’ technical efficiency

In a second stage, we assume that variations in cooperatives’ efficiency levels is explained by variations in cooperatives’ own characteristics and that of its neighbors. A model that incorporates these effects can be represented by the following truncated regression model:

\[
TE = Z\beta + WZ\delta + \epsilon,
\]

where \( TE \) denotes an \( N \times 1 \) vector consisting of the cooperative-specific technical efficiency scores obtained by solving equation (2), \( Z \) is an \( N \times K \) matrix of covariates that may affect technical efficiency, \( W \) is an \( N \times N \) spatial weighting matrix (defined below), \( \beta \) and \( \delta \) are \( K \times 1 \) vectors of unknown parameters to be estimated, and \( \epsilon \) is an \( N \times 1 \) vector of disturbance terms. Spatial econometricians refer to \( WZ \) as “the spatial lags of the explanatory variables”. For each observation \( i \), \( w_i'Z \) is a linear combination of all \( Z_j \) with which the \( i \)-th observation is connected (Gibbons & Overman, 2012). Therefore, \( \delta \), which is known as the indirect or spillover effect, captures how a cooperative’s efficiency changes when particular explanatory variables in neighboring cooperatives change. On the other hand, \( \beta \), which is known as the direct effect, captures the change in a cooperative’s efficiency attributable to changes in the explanatory variables of that cooperative itself. When \( \delta = 0 \) the model in (4) reduces to the nonspatial truncated regression model.

The model in (4) is known, in the spatial econometrics literature, as the spatial (lag of) X model (SLX), and it can be viewed as a reduced form of the so-called spatial autoregressive model (SAR). The SLX model assumes that the neighbors’ characteristics (not the outcomes) are relevant for a firm’s own outcome. This is true in our case since the technical efficiency of neighboring cooperatives (i.e., \( w_i' TE \)) is hard to observe, but what can be observed and, consequently, affect a cooperative’s input-output allocations and performance, is the characteristics and decisions of neighboring cooperatives (i.e., \( w_i' Z \); e.g., product differentiation strategy, export decisions, etc.). In support of this argument, Maté-Sánchez-Val et al. (2017) argue that, in conditions of high uncertainty, firms will track the decisions of geographically proximate peer firms in an attempt to overcome the informational limitations that hamper their ability to make optimal decisions. Moreover, access to information about the decisions and characteristics of geographically proximate peer firms may be facilitated by the contact between the managers of these firms through professional and social mechanisms (e.g., social and professional clubs, educational experiences, etc.; Davis & Greve, 1997; McMullin, 2016, Maté-Sánchez-Val et al., 2017). Therefore, we argue that the SLX model may better capture the connections between cooperative \( i \) and its neighbors. Gibbons and Overman (2012) argue that in many situations the SLX model is more credible and the parameters of the spatially lagged exogenous variables are useful and policy-relevant since they provide information on the likely channels through which the spatial effects operate.

The model in (4) was estimated using the single bootstrap approach of Simar and Wilson (2007) (i.e., Algorithm 1). The reason behind using this approach was to address the well-known problem of serial correlation among

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1The SAR model in our case can be written as follows: \( TE = \beta WTE + Z\delta + \epsilon \). A reduced form of this model implies expressing \( TE \) in terms of exogenous factors (Gibbons & Overman, 2012).
non-parametrically derived efficiency scores (Simar & Wilson, 2007). The single bootstrap approach is commonly used in the analysis of the determinants of technical efficiency of agricultural decision-making units, including cooperatives (e.g., Huang et al., 2013) and farms (e.g., Skevas, Lansink, & Stefanou, 2012; Skevas & Serra, 2016). The steps of the single bootstrap approach are as follows. First, the method of maximum likelihood was used to estimate the truncated regression of $\text{TE}$ on $Z$ and $WZ$ in (4)$^2$ to obtain estimates $\hat{\beta}$ of $\beta$, $\hat{\delta}$ of $\delta$, and $\hat{\sigma}_\epsilon$ of the standard deviation of the error term ($\epsilon_i$). Second, the following steps were replicated 1,000 times to obtain a set of bootstrap estimates $(\hat{\beta}, \hat{\delta}, \hat{\sigma}_\epsilon)$, with $n = 1, ..., 1000$: (a) for each observation $i$, a residual $\epsilon_i$ was drawn from the $N(0, \sigma^2)$ distribution with left truncation at $\beta\delta Z$; (b) the adjusted efficiency score $\tilde{\text{TE}}$ was computed as follows: $\tilde{\text{TE}} = Z\hat{\beta} + WZ\hat{\delta} + \epsilon_i$; (c) a truncated regression of $\tilde{\text{TE}}$ on $Z$ and $WZ$ was performed using maximum likelihood to obtain a set of values $(\tilde{\beta}, \tilde{\delta}, \tilde{\sigma}_\epsilon)$. Finally, the bootstrap estimates and the original estimates were used to construct estimated confidence intervals for $\beta$, $\delta$, and $\sigma$. A more detailed description of the single bootstrap truncated regression can be found in Simar and Wilson (2007).

3 | DATA AND EMPIRICAL SPECIFICATION

The data used in this study come from Cooperative Programs, a division of the Rural Business-Cooperative Service (RBS) in the USDA Office of Rural Development. Each year, the division surveys the full population of farmer, fisher, and rancher cooperatives in the United States and reports the responses in aggregate form in its annual publication (USDA, 2015). The data set contains basic information from the balance sheet and income statement. In addition, we collected information from Secretaries of State and the U.S. Patent and Trademark Office to inform socioeconomic characteristics (e.g., age, location, etc.). The data set used here contains information on 368 grain cooperatives in Midwestern states of the US from the fiscal year 2014.$^3$ Figure 1 presents the geographic distribution of the sample cooperatives by state. Of the 12 states used in this study, the state with the highest number of grain marketing cooperatives is Kansas with 58; Wisconsin has the fewest with 5.

Before discussing the data collected from the above-mentioned sources, it is worth providing some background information on U.S. grain marketing cooperatives. Grain marketing cooperatives have a dominant presence in the U.S. grain sector. For example, 404 of the 589 grain elevator locations in Iowa, which in 2014 produced the most corn (2.4 billion bushels) and the second-most soybeans (498 million bushels), are owned and controlled by cooperatives (Grashuis, 2019). In the year of our study (i.e., 2014), the total population of U.S. grain marketing cooperatives reported almost $57.9 billion in net sales, whereas the most recent data from 2017 show that these sales decreased to $46.6 billion (U.S. Department of Agriculture, 2017). In 2017, U.S. grain marketing cooperatives had approximately 400,000 members and 24,000 full-time employees. In recent history, many grain marketing cooperatives have been merging among themselves to achieve scale economies (Merlo, 2017). Often, there are spatial motivations and repercussions to such strategic interactions (Grashuis & Elliott, 2018), although merger and acquisition activity in the other stages of the agri-food value chain also play a substantial role. Grain marketing cooperatives face challenges stemming from the external environment in which they operate. For instance, volatility in corn and soybean prices makes financial planning and expectations challenging. Another challenge is linked to the volatility in international trade policies, which increases the uncertainty regarding the number of export partners and shares.

Moving to the description of the collected data, one output and three inputs were obtained. The output represents the total sales to grain buyers. The inputs include raw materials, fixed assets, and other inputs. Raw materials represent the cost of purchasing the input material (i.e., grain). Fixed assets are measured as the value of

$^3$In the regression, it was assumed that $\epsilon_i \sim N(0, \sigma^2)$ with left-tail truncation at $1 - Z\beta - WZ\delta$.

$^3$These states are Illinois, Iowa, Kansas, Missouri, North and South Dakota, Nebraska, Wisconsin, Michigan, Ohio, Indiana, and Minnesota.
plant, property, and equipment. Other inputs, consist of labor expenses, depreciation, interest expenses, and other expenses. The input-output data described above are used to empirically specify Equation (3).

Our selection of factors ($Z$) that may influence cooperatives' output technical efficiency is on the basis of data availability and previous research on cooperatives' efficiency (Huang et al., 2013; Ariyaratne et al., 2000) and includes the following variables: Cooperative size, measured as the number of members (members); leverage measured as the ratio of total liabilities to total assets (leverage); liquidity, measured as the ratio of current assets to current liabilities (liquidity); age measured by the number of years of operation (age); a dummy variable, which takes the value of 1 if a cooperative has at least one trademark, and 0 otherwise (differentiation); and a dummy variable, which takes the value of 1 if a cooperative has positive export sales, and 0 otherwise (export).

**TABLE 1** Descriptive statistics of the study variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Units</th>
<th>Mean</th>
<th>Std.dev</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output</td>
<td>$1,000,000</td>
<td>289</td>
<td>2300</td>
<td>12.19</td>
<td>42664.03</td>
</tr>
<tr>
<td>Fixed assets</td>
<td>$1,000,000</td>
<td>27.30</td>
<td>213</td>
<td>0.33</td>
<td>4031.02</td>
</tr>
<tr>
<td>Raw materials</td>
<td>$1,000,000</td>
<td>270</td>
<td>2210</td>
<td>10.72</td>
<td>41016.80</td>
</tr>
<tr>
<td>Total expenses</td>
<td>$1,000,000</td>
<td>14.80</td>
<td>47.20</td>
<td>0.31</td>
<td>737.54</td>
</tr>
<tr>
<td>Leverage</td>
<td>ratio</td>
<td>0.54</td>
<td>0.15</td>
<td>0.01</td>
<td>1</td>
</tr>
<tr>
<td>Liquidity</td>
<td>ratio</td>
<td>1.60</td>
<td>1.05</td>
<td>0.10</td>
<td>13.79</td>
</tr>
<tr>
<td>Export</td>
<td>(0/1)</td>
<td>0.04</td>
<td>0.20</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Differentiation</td>
<td>(0/1)</td>
<td>0.08</td>
<td>0.28</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Age</td>
<td>years</td>
<td>79.95</td>
<td>29.56</td>
<td>4</td>
<td>128</td>
</tr>
<tr>
<td>Members</td>
<td>count/100</td>
<td>12.10</td>
<td>37.44</td>
<td>0.34</td>
<td>694.45</td>
</tr>
</tbody>
</table>
Table 1 presents summary statistics for the variables used in this study. Below we discuss how each of the above factors may influence the output technical efficiency of cooperatives.

3.1 | Factors that may influence cooperatives' output technical efficiency

3.1.1 | Cooperative size

Cooperative size (as measured by the number of members) is associated with a superior ability to bargain with buyers and find more or better marketing opportunities. In turn, better marketing opportunities may result in higher sales and increased output efficiency. On the other hand, since most cooperatives have an open membership policy and must, therefore, accept all supplies they may face an oversupply of products. This may lead some cooperatives to face difficulties in marketing all their products or to choose to market their products at lower prices, thus leading to lower sales and, as a result, lower output efficiency. Therefore, the influence of cooperative size on output technical efficiency is ambiguous.

3.1.2 | Leverage

The amount of leverage (or debt to total assets) that cooperatives carry is expected to affect their output technical efficiency. High debt may divert attention from member business activities and make decisions depending on cash-flow considerations, thus leading to suboptimal business decisions. Such considerations may cause a negative impact of leverage on technical efficiency, as found by Huang et al. (2013) in relation to Chinese marketing cooperatives’ input-oriented technical efficiency. However, as cooperatives in general face capital constraints, a relatively high degree of leverage may reflect investments in storage or transport to facilitate improvements in output and sales quantity and quality, which are otherwise not attainable. The influence of leverage on the output technical efficiency appears to be ambiguous.

3.1.3 | Liquidity

High liquidity, which is indicative of greater financial flexibility, may facilitate investments in infrastructure, new technologies, and business opportunities and result in increased sales and output efficiency. At the same time, however, the short-term asset portfolio (reflected in the current assets part of our liquidity indicator) may be composed of grain inventories, which are not sold on the output market, thus resulting in decreased sales and, as a result, lower output efficiency. Therefore, the effect of liquidity on output efficiency is an issue that warrants empirical investigation. In a study that explores the determinants of technical efficiency of Great Plains grain marketing and farm supply cooperatives, Ariyaratne et al. (2000) did not find a significant effect of liquidity (as measured by the current ratio) on technical efficiency.

3.1.4 | Cooperative's age

Corresponding to the “liability of newness” and “liability of adolescence” perspectives (Bruderl & Schussler, 1990), age proxies experience but also inertia. Relatively young grain marketing cooperatives may lack knowledge of the market to find access to buyers, and this may result in lower output efficiency. On the other hand, relatively old grain marketing cooperatives may lack the flexibility to adapt appropriately to rapid evolutions in the dynamic marketplace, which can impact negatively their output efficiency. Therefore, since both positive and negative impacts can be expected a priori, the actual impact of age on output efficiency is an empirical question.
3.1.5 | Differentiation

Differentiation, which in our study reflects the ownership of trademarks, is one of several strategies that cooperatives pursue to obtain a competitive advantage that can lead to increased sales and, as a result, higher output efficiency. Trademark ownership is used frequently in the recent empirical literature to proxy brand equity and similar constructs (Schautschick & Greenhalgh, 2016). Generally, trademark ownership is related positively to the financial performance of marketing cooperatives (Grashuis, In press). Therefore, we expect cooperatives with higher differentiation to have increased revenues and output technical efficiency.

3.1.6 | Export orientation

Export orientation, which in our study reflects positive export sales, implies a greater available number of buyers. The domestic market has fewer buyers, many of whom are relatively large and may not transact with many different grain marketing cooperatives. We hypothesize that cooperatives with positive export sales will have higher total sales and, as a result, higher output technical efficiency.

3.2 | Spatial weighting matrix

The spatial weighting matrix (i.e., W), which describes the spatial configuration of cooperatives in the sample, is specified using an inverse distance matrix. This choice is motivated by the fact that an inverse distance matrix places a higher weight on closer than more distant neighbors. The diagonal elements of W are set to zero by assumption, since no cooperative can be viewed as its own neighbor. The off-diagonal elements \( w_{ij} \) are set equal to \( 1/d_{ij} \), where \( d_{ij} \) is the Euclidian distance between cooperative \( i \) and \( j \), if two cooperatives operate within a certain distance, and 0 otherwise. The minimum distance cut-off was set as the minimum distance that all cooperatives in our sample have at least one other cooperative as a neighbor, which is 150 km in our sample. Sensitivity analysis with respect to the distance cut-off point was performed using a variety of alternative cut-off points (i.e., 100, 180, and 200 km) as in Skevas, Skevas, and Swinton (2018). We follow common practice and normalize \( W \) by dividing each of its elements by its largest characteristic root (Elhorst, 2001; Kelejian & Prucha, 2010).

4 | RESULTS

4.1 | Technical efficiency of grain cooperatives

Table 2 presents the results of the technical efficiency of grain marketing cooperatives. The results show that the average technical efficiency is 1.113, ranging from a minimum of 1 to a maximum of 1.302. This result implies that cooperatives can, on average, increase their output by \( 10.2\% \) \( (1 - 1/1.113)^*100 \) without altering the input quantities used.

Figure 2 presents a histogram of the technical efficiency estimates. Efficient cooperatives (i.e., cooperatives with a TE score of 1) comprise around 4 percent of the sample. The largest group of inefficient cooperatives (i.e., 59 percent) lies between 1.1 and 1.2.

To obtain a spatial picture of the technical efficiency, the TE values are plotted on a map (Figure 3). This figure shows the spatial pattern of estimated technical efficiency scores. The pattern of efficient cooperatives is quite

| TABLE 2 | Descriptive statistics of estimated efficiency of grain cooperatives |
|---------|-----------------|-----------------|---------------|-------------|-------------|
|         | Mean | Median | Std. deviation | Min | Max |
| TE      | 1.113 | 1.114 | 0.052 | 1.000 | 1.302 |
dispersed. In contrast, geographic clusters of relatively highly inefficient cooperatives appear to exist in the states of Kansas and Illinois, the northern corners of the states of Iowa and Ohio, and along the western borders of Minnesota. These clusters may reflect the presence of spatial dependence in nearby cooperatives’ technical efficiency and reveal the locations of cooperatives that may have reason to address inefficiency. However, these

**FIGURE 2** Histogram of the technical efficiency estimates

**FIGURE 3** Spatial pattern of technical efficiency
observations may also operate in spaces or markets where conditions of imperfect competition, which often constitute the initial motivation to engage in collective action, still prevail.

4.2 Explaining grain marketing cooperatives’ technical efficiency

In this section, the results are presented with and without spatial interdependence. By distinguishing between the nonspatial and spatial truncated regression model (SLX), we can explore whether or not spatial spillovers exist. Results for both models are presented in Table 3. Because the spatial model nests the nonspatial model, we can use the Akaike Information Criteria (AIC) to choose between the two models. It is apparent from Table 3 that the spatial model (SLX) is the preferred model because it has a lower AIC value compared to the nonspatial model indicating a better fit. We can also see from Table 3 that some of the coefficients of the spatially lagged variables are significant, indicating the presence of spatial spillover effects in the technical efficiency of neighboring cooperatives.

Because the coefficients reported in Table 3 only indicate the direction of the effect that the explanatory variables have on technical efficiency, we further derived the marginal effects to show the magnitude of response to a change in an explanatory variable. The marginal effects from both models are reported in Table 4. The remainder of the discussion in this subsection focuses on interpreting the marginal effects of the preferred SLX model rather than the raw truncated regression coefficients. Notice that there are only small differences between the estimated marginal effects of the non-spatially lagged variables in the two models. Hence, the interpretation of these marginal effects (in terms of the direction of the effects) applies to both models that are presented in Table 4.

The marginal effects of the non-spatially lagged regressors and their confidence intervals (CI) are presented in the upper half of Table 4. It should be noted here that if a factor is positively (negatively) associated with efficiency, its marginal effect will be negative (positive) as we used a DEA output-oriented approach, which yielded efficiency estimates that take values from one to positive infinity. Statistical significance is indicated when the confidence interval does not contain zero.

Technical efficiency of grain marketing cooperatives is related significantly to four variables: Liquidity, differentiation, age, and membership size. Liquidity is found to enhance technical efficiency, indicating a one unit increase in the ratio of current assets to current liabilities would increase technical efficiency by 1.4%. Liquidity is an indicator of a cooperative’s ability to pay back its short-term liabilities. The higher the liquidity the more capable a cooperative is of fulfilling its financial obligations in the near future, indicating good financial health. In turn, a cooperative with good financial health will be more capable of allocating scarce resources to the marketing of grain as opposed to the payment of the debt.

In contrast to this study, Ariyaratne et al. (2000) did not find a significant effect of the current ratio (which is an indicator of liquidity) on technical efficiency in their study of the efficiency analysis of Great Plains grain marketing and farm supply cooperatives.

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Technical efficiency of grain marketing cooperatives is related significantly to four variables: Liquidity, differentiation, age, and membership size. Liquidity is found to enhance technical efficiency, indicating a one unit increase in the ratio of current assets to current liabilities would increase technical efficiency by 1.4%. Liquidity is an indicator of a cooperative’s ability to pay back its short-term liabilities. The higher the liquidity the more capable a cooperative is of fulfilling its financial obligations in the near future, indicating good financial health. In turn, a cooperative with good financial health will be more capable of allocating scarce resources to the marketing of grain as opposed to the payment of the debt.

In contrast to this study, Ariyaratne et al. (2000) did not find a significant effect of the current ratio (which is an indicator of liquidity) on technical efficiency in their study of the efficiency analysis of Great Plains grain marketing and farm supply cooperatives.

In terms of differentiation (or strategic orientation), we find that ownership of trademarks is positively related to technical efficiency. More specifically, cooperatives that have at least one trademark have an expected increase of 0.023 in their technical efficiency. Most grain marketing cooperatives may not be able to pursue product
| TABLE 3 Truncated regression results of the nonspatial and spatial (SLX) models. Estimated parameters and bootstrapped confidence intervals |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Nonspatial model | | | | | Spatial model (SLX) | | | | | |
| | Coef. | 95% CI | 90% CI | Coef. | 95% CI | 90% CI | Coef. | 95% CI | 90% CI | Coef. | 95% CI | 90% CI |
| Const. | 1.168 | 1.133 | 1.205 | 1.138 | 1.200 | 1.155 | 1.115 | 1.198 | 1.121 | 1.190 |
| Leverage | -0.018 | -0.056 | 0.018 | -0.048 | 0.012 | -0.006 | -0.045 | 0.032 | -0.039 | 0.032 |
| Liquidity | -0.014 | -0.023 | -0.007 | -0.021 | -0.008 | -0.014 | -0.023 | -0.006 | -0.021 | -0.006 |
| Export | 0.003 | -0.022 | 0.028 | -0.017 | 0.024 | 0.007 | -0.020 | 0.034 | -0.014 | 0.034 |
| Differentiation | -0.027 | -0.049 | -0.007 | -0.045 | -0.011 | -0.030 | -0.051 | -0.010 | -0.048 | -0.010 |
| Age | -0.001 | -0.002 | -3.10^{-4} | -0.002 | -5.10^{-4} | -0.001 | -0.002 | -2.10^{-4} | -0.002 | -2.10^{-4} |
| Age$^2$ | 8.10^{-6} | 3.10^{-6} | 10^{-5} | 4.10^{-6} | 10^{-5} | 7.10^{-6} | 7.10^{-7} | 4.10^{-5} | 2.10^{-6} | 10^{-5} |
| Members | 0.021 | 0.009 | 0.033 | 0.011 | 0.031 | 0.018 | 0.005 | 0.031 | 0.008 | 0.031 |
| Members$^2$ | -0.005 | -0.008 | -0.002 | -0.007 | -0.003 | -0.004 | -0.007 | -0.002 | -0.007 | -0.002 |
| W_Leverage | - | - | - | - | - | 2.10^{-4} | -0.161 | 0.167 | -0.133 | 0.167 |
| W_Liquidity | - | - | - | - | - | -0.035 | -0.063 | -0.008 | -0.057 | -0.008 |
| W_Export | - | - | - | - | - | 0.124 | -0.044 | 0.301 | -0.017 | 0.301 |
| W_Differentiation | - | - | - | - | - | -0.173 | -0.320 | -0.023 | -0.297 | -0.023 |
| W_Age | - | - | - | - | - | -2.10^{-4} | -0.005 | 0.005 | -0.004 | 0.005 |
| W_Age$^2$ | - | - | - | - | - | 4.10^{-6} | -4.10^{-5} | -4.10^{-5} | -3.10^{-5} | -4.10^{-5} |
| W_Members | - | - | - | - | - | 0.075 | 0.032 | 0.118 | 0.040 | 0.118 |
| W_Members$^2$ | - | - | - | - | - | -0.001 | -0.002 | 10^{-3} | -0.002 | 10^{-3} |
| AIC | -1226.54 | | | | | -1265.72 | | | | |

Note: The dependent variable is the output-oriented technical efficiency scores. Spatially lagged variables are denoted with a leading "W_". Statistically significant confidence intervals are in bold. AIC stands for Akaike’s Information Criterion.
## Table 4 Marginal effects of the determinants of technical efficiency for the nonspatial and spatial models

<table>
<thead>
<tr>
<th></th>
<th>Nonspatial model</th>
<th>Spatial model (SLX)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>Lower bound</td>
</tr>
<tr>
<td>Leverage</td>
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<td>-0.056</td>
</tr>
<tr>
<td>Liquidity</td>
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<td>-0.023</td>
</tr>
<tr>
<td>Export</td>
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<td>-0.022</td>
</tr>
<tr>
<td>Differentiation</td>
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<td>-0.049</td>
</tr>
<tr>
<td>Age</td>
<td>-0.001</td>
<td>-0.002</td>
</tr>
<tr>
<td>Age^2</td>
<td>7.10^-6</td>
<td>2.10^-6</td>
</tr>
<tr>
<td>Members</td>
<td>0.019</td>
<td>0.032</td>
</tr>
<tr>
<td>Members^2</td>
<td>-0.004</td>
<td>-0.002</td>
</tr>
<tr>
<td>W_Leverage</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>W_Liquidity</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>W_Export</td>
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<td>-</td>
</tr>
<tr>
<td>W_Differentiation</td>
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<tr>
<td>W_Age</td>
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<tr>
<td>W_Age^2</td>
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<td>W_Members</td>
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<td>-</td>
</tr>
<tr>
<td>W_Members^2</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Note: Marginal effects for continuous variables are estimated at their mean values, while those for dummy variables are calculated as discrete change from 0 to 1. Spatially lagged variables are denoted with a leading “W.” Statistically significant confidence intervals are in bold.
differentiation (Bijman, 2016), but the result indicates the importance of developing a distinctive brand or service. Such differentiation may facilitate more or better marketing opportunities so as to increase either grain quantity or price. Our result corresponds to recent findings by Grashuis (In press), who reported a positive relationship of brand equity to the financial performance of marketing cooperatives in the United States.

Moving to the effect of the age variable on technical efficiency, we observe that older cooperatives are more efficient (i.e., they have an expected increase of 0.1% in their technical efficiency), likely because of superior experience in the area of sales and marketing as compared with their younger counterparts. As compared with relatively old cooperatives, relatively young cooperatives may lack secure connections or partnerships with grain buyers. The positive and significant marginal effect of the age variable in conjunction with the negative and significant marginal effect of the age squared variable imply that cooperatives’ technical efficiency increases at a decreasing rate as age of the cooperative increases. The latter effect may be the result of inertia or other types of problems common to older business organizations. Overall, the exponential relationship of age to technical efficiency corresponds to the general interpretation of the cooperative life cycle model (Cook, 2018), which relates the performance of cooperatives to the ability to adapt to various developments in the internal and external environment.

Finally, the impact of membership size on technical efficiency is negative and decreases with increasing size. This result may be attributed to an oversupply of products because of the cooperatives’ open membership policy, which implies an obligation for cooperatives to process all their members’ supplies (i.e., raw materials). Faced with such oversupply, some cooperatives may encounter difficulties in marketing all their raw materials or may choose to market their increased goods at a lower price. However, at a very large membership size, the negative effect on output efficiency is reversed, likely because of the superior ability of very large cooperatives to bargain with large buyers.

We now turn to the interpretation of the spatially lagged explanatory variables (lower half of Table 4). Of the spatially lagged variables included in the SLX model, three were found to be statistically significant. The spatial lag of liquidity, differentiation, and membership size were significantly related to technical efficiency. Cooperatives with neighbors that have high liquidity are able to achieve higher levels of output technical efficiency (i.e., a 3.4% increase in their technical efficiency). A reason for this finding could be that since firms with high liquidity are more able to invest resources to the improvement of their marketing systems, geographically proximate cooperatives would learn from these investments by observing success or failure, leading to more optimal marketing strategies.

The marginal effect of the spatial lag of the differentiation variable is $-0.17$, implying that cooperatives that are surrounded by neighbors that have at least one trademark experience have an expected increase of 0.17 in their technical efficiency. Because trademarks indicate, among other attributes, preferred quality characteristics of identified products and given the high probability that geographically proximate cooperatives source their raw materials from the same location, a positive reputation spillover effect may occur and impact positively the sales of nearby cooperatives.

Finally, cooperatives with larger neighbors in terms of members (everything else being equal) have an expected decrease of around 7% in their technical efficiency. This result may be attributed to spatial competition for securing raw materials, which may incur additional search costs and lower the financial resources available for improving sales and marketing effectiveness. Also, these larger neighbors are more likely to secure the finite amount of sales contracts with buyers. Larger cooperatives have greater market access and bargaining power. There may not be enough demand for grain from smaller cooperatives.

5 | CONCLUSIONS

This study used a DEA model followed by a truncated bootstrap regression model to examine the role of spatial spillovers (and other relevant factors) on cooperatives' output technical efficiency. The application focuses on financial and socioeconomic data from grain marketing cooperatives in the US Midwest and provides evidence of the existence of spatial spillovers in nearby cooperatives' technical efficiency.
Four important conclusions can be drawn from the results of this study. First, spatial spillovers play an important role in explaining changes in nearby cooperatives’ technical efficiency. The likely channels through which these effects operate relate to positive externalities associated with higher levels of liquidity and differentiation, and negative externalities associated with higher membership size. These results imply that future studies examining the determinants of cooperatives’ efficiency should be sensitive to the influence of spatial spillovers in addition to own-firm characteristics. Second, there is scope for increasing grain marketing cooperatives’ technical efficiency. More specifically, grain marketing cooperatives can, on average, increase their outputs by around 10 percent while keeping inputs constant. This result implies that there exist a fair amount of grain marketing cooperatives, which may benefit from various efficiency-enhancing strategies devised by either managers, external stakeholders, or policymakers. Third, there exist spatial clusters of grain marketing cooperatives, which exhibit relatively high technical inefficiency. These clusters, which are situated in Kansas, Illinois, and parts of Iowa, Minnesota, and Ohio, indicate the location of grain marketing cooperatives, which may seek opportunities to improve efficiency. The relative inefficiency of these observations may relate to the local or regional environment, which implies it may also be addressed by external stakeholders and policymakers. Fourth, apart from processes that take place at the neighborhood level, we also find that grain marketing cooperatives’ technical efficiency is influenced at the cooperative firm-level. More specifically, we find older grain marketing cooperatives with strong liquidity and some degree of differentiation have relatively high technical efficiency, while larger cooperatives in terms of membership size have lower technical efficiency.

Finally, there are some limitations in this study that need to be acknowledged. First, our analysis cannot empirically determine through which channels the interdependence between cooperatives arises. Instead, it uses the results of the spatially explicit analysis and theoretical considerations to provide information on the likely channels of cooperative interactions. Thus, empirically assessing the channels through which spatial interdependencies might affect neighboring cooperatives’ technical efficiency would be an interesting avenue for future research endeavors. Second, cooperatives’ technical efficiency is analyzed at one point in time, but it is likely that cooperatives are influenced by previous decisions of nearby cooperatives. Hence, extending this study to a panel setting would be another interesting area for future research. The employment of panel data will also allow to control for time-invariant cooperative effects and additional dynamic components that may affect cooperatives’ technical efficiency (e.g., changes in output prices).

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