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Does the Tennessee Master Beef Producer Program Impact Technical Efficiency?

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Abstract
The impacts of the Tennessee Master Beef Producer (MBP) program on the technical efficiency (TE) of Tennessee beef production was estimated using county-level data in 2007, 2012, and 2017. A two-stage, double bootstrap method was used to measure TE by county and year, and identify any statistical relationship between MBP and TE. TE of beef production changed statewide during this time period. We found a positive relationship in MBP participation and county-level TE of beef production. Results are helpful in targeting locations for future education and provide evidence on the effectiveness of MBP.

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Introduction

Recognizing the importance of Tennessee beef production, University of Tennessee (UT) Extension launched a county-level educational program called Master Beef Producer (MBP) in 2004. This program began as a 12-session course that covers topics such as marketing and economics, forages, health, reproduction, and nutrition to name a few. While participation for MBP started slow, a key moment in MBP success occurred in 2007 when the Tennessee Department of Agriculture allowed certified MBPs access to the Tennessee Agricultural Enhancement Program fund, which provides partial cost-reimbursement for qualified purchases.

The purpose of MBP is to instruct Tennessee cattle producers about best practices to sustain their long-term profitability and increase beef production. A commonly used economic measurement to evaluate long-term profitability, or growth and survival of firms, is technical efficiency (TE) (Farrell, 1957). TE is generally defined as how effective a firm or decision-making unit (DMU) is at maximizing output from a given bundle of inputs or to produce a given level of output while minimizing inputs. Agricultural economists have a long history of analyzing the TE of various crop and livestock production systems (Morrison Paul et al., 2004).

Data envelopment analysis (DEA) is commonly used to measure TE (Charnes, Cooper, and Rhodes, 1978) but this approach cannot explain what causes the changes in TE. Therefore,

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researchers have used a two-stage DEA to determine the TE of evaluated targets, and examine the statistical relationships between TE and environmental/exogenous variables (Vitale, Vitale, and Epplin, 2019; Watkins et al., 2014).

This research explores changes in TE in beef production across Tennessee over time and measures the impacts of the MBP on beef production TE. If the program is found to be effective, this would demonstrate a successful educational program which could be adopted by Extension services across the United States. Also, to our knowledge, no study has assessed how an Extension program like MBP impacts TE for any commodity. Thus, we provide a robust framework for others to measure the effectiveness of state Extension programs.

Data

County-level data were collected from the 2007, 2012 and 2017 United States Department of Agriculture (USDA) Census of Agriculture (USDA National Agricultural Statistical Service [NASS], 2019) for all inputs and outputs of the DEA. Since pasture and hay are vital inputs in Tennessee beef production, inputs for our model include the average pasture acres per operation, hay acres per operation, and head per operation for each county (Henry et al., 2016). These were generated by dividing the total number of pasture acres (excluding cropland and woodland), hay/haylage acres, and cattle inventory (including calves) for each county by the total number of beef cattle operations within the county. Tennessee has a total of 95 counties, but not all the data were available for all these counties. Therefore, we dropped counties from the dataset that were not in all three years of the data, which left 82 counties or DMUs per year.

The output variable for our analysis was total pounds of beef sold per operation by county. This was determined by first generating total market receipts of beef sold per operation by county, which was calculated by dividing total market receipts for beef sales in each county by the total number of beef operations in each county. The next step was dividing the total market receipts of beef sold per operation in a county by the average price of 500-600 lb. feeder cattle sold in Tennessee in 2007, 2012, and 2017. Tennessee prices were $1.21/lb. in 2007, $1.47/lb. in 2012, and $1.39/lb. in 2017 (USDA Agricultural Marketing Service, 2019) and all prices were adjusted into 2017 dollar values using the Implicit Gross Domestic Product Price Deflator (United States Bureau of Economic Analysis, 2019). Table 1 shows the summary statistics for the input and output variables by year.

Exogenous/environmental variables in the second-stage regression included the percentage of MBP certificates relative to the number of beef cattle operations within each county. The aggregate number of certificates provided from 2008 to 2012 were used in the 2012 dataset, and the aggregate number of MBP certificates from 2013 to 2017 were assumed for the 2017 dataset. We then divided this aggregated number of MBP certificates within a county by the total number of beef operations within the same county over the same time periods. The total number of certificates awarded during this time period was 11,984 with 3,176 occurring from 2008-2012 and 8,808 being awarded from 2013 to 2017.

Table 1. Average of All County-Level Summary Statistics of Output and Input Variables in Tennessee from 2007, 2012, and 2017, United States Department of Agriculture Agricultural Census Data

Variables	Year	Mean	Standard Deviation	Minimum	Maximum
		Output Variable			
Pounds per Operation	2007	13,420	3,933	6,810	25,738
	2012	15,533	7,229	6,403	43,080
	2017	16,860	8,075	5,619	50,858
		Input Variables			
Pasture Acres per Operation	2007	66.84	15.95	37.46	105.99
	2012	91.10	22.23	55.16	153.00
	2017	87.32	22.47	46.32	161.03
Hay Acres per Operation	2007	46.60	8.62	31.85	74.00
	2012	54.27	10.94	33.20	89.07
	2017	54.33	9.14	36.43	85.59
Herd Size per Operation	2007	54.52	10.62	36.54	83.99
	2012	56.21	12.96	35.41	99.29
	2017	59.30	14.89	31.13	108.68

[a] Receipts are adjusted in 2017 dollars

We also included year dummy variables and regional location dummy variables. Regions were divided following the UT Extension Regional office lines (UT Extension, 2019). Figure 1 shows the average number of MBP certificates per county by region. In 2012, an average county in East Tennessee had 26 certified MBP operations and, in 2017, that number increased to an average of 71 operations per county in the eastern region. For all regions, the average number of MBP certificates increased from 2012 to 2017.

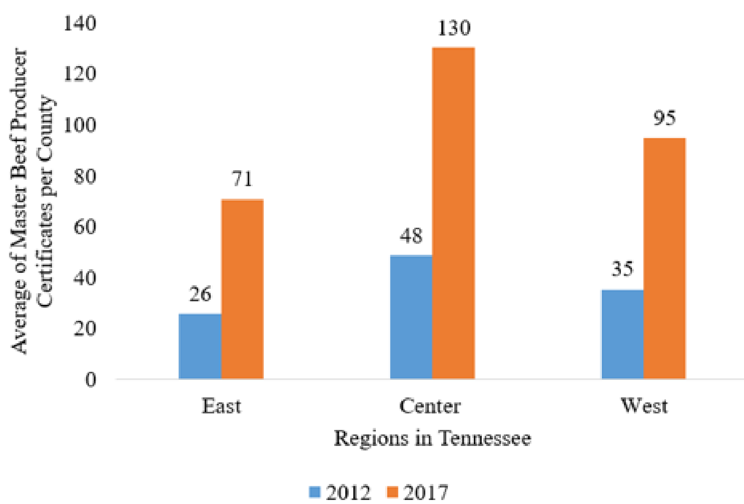

Figure 1. Average Number of Master Beef Producer Certificates Awarded per County by Region

Methods

The first stage DEA determined the technically efficient counties for cattle in Tennessee for each individual year. We followed Olson and Vu (2009) by using an output-based model since inputs in our model (acres and cows) are fixed in the short term and producers are maximizing their outputs. We assumed counties had variable returns-to-scale since previous studies had identified farms typically have increasing, decreasing, and constant returns-to-scale (Morrison Paul et al., 2004; Vitale, Vitale, and Epplin, 2019). Under this assumption, the DEA model has a constraint that the frontier function is convex envelopment.

When analyzing the impact of environmental/exogenous variables on DEA estimates for a two-stage analysis, a typical approach in the second stage is to use a Tobit or truncated regression model (Vitale, Vitale, and Epplin, 2019; Watkins et al., 2014). We followed the double bootstrap procedure developed by Simar and Wilson (2007), and specifically used the procedure of Algorithm 2, which uses maximum likelihood to estimate a truncated regression. All three years of the data were combined to estimate the second stage regression. Following Simar and Wilson (2007), the output dependent variable is the inefficiency index, which is the reciprocal of the TE score. A positive parameter estimate indicates that increasing the independent variable will decrease TE. Conversely, a negative parameter estimate indicates that increasing the independent variable will increase TE.

We should note studies using this method typically have panel or survey data, allowing them to estimate the impact of demographic variables on TE. Our study uses county-level data, which aggregates individuals within a county to the county-level. Aggregated data have been used in analyzing relative efficiency between counties or states in previous studies (Helfand and Levine, 2004). A possible limitation of these data is over-estimating the impact of the environmental variables in the second stage. Thus, our results are limited by not having individual level data, and results could overestimate the magnitude of the parameters in the second stage.

Results

Figure 2 maps the TE scores of cattle production by county over the three years. As mentioned, TE is interpreted relative to the most efficient county within the sample being compared. All the counties could still improve efficiency, but the TE score shows which counties are less efficient relative to the most efficient at that time period. The technically efficient counties in 2007 were primarily located in East Tennessee and one was located in Central Tennessee. None of the counties in West Tennessee reached the efficiency frontier. A similar pattern is observed in 2012 with four technically efficient counties located in East Tennessee, one in the central, and none in the west region. However, in 2017, only two counties in East Tennessee achieved ideal efficiency, while three counties in Central Tennessee were on the efficiency frontier. In addition, the number of less efficient counties (TE ≤ 0.49) in East Tennessee has increased over time, while the less efficient counties in the central and west regions have clearly improved between 2012 and 2017. This could be related to the increasing participation of MBP in those two regions (see Figure 1).

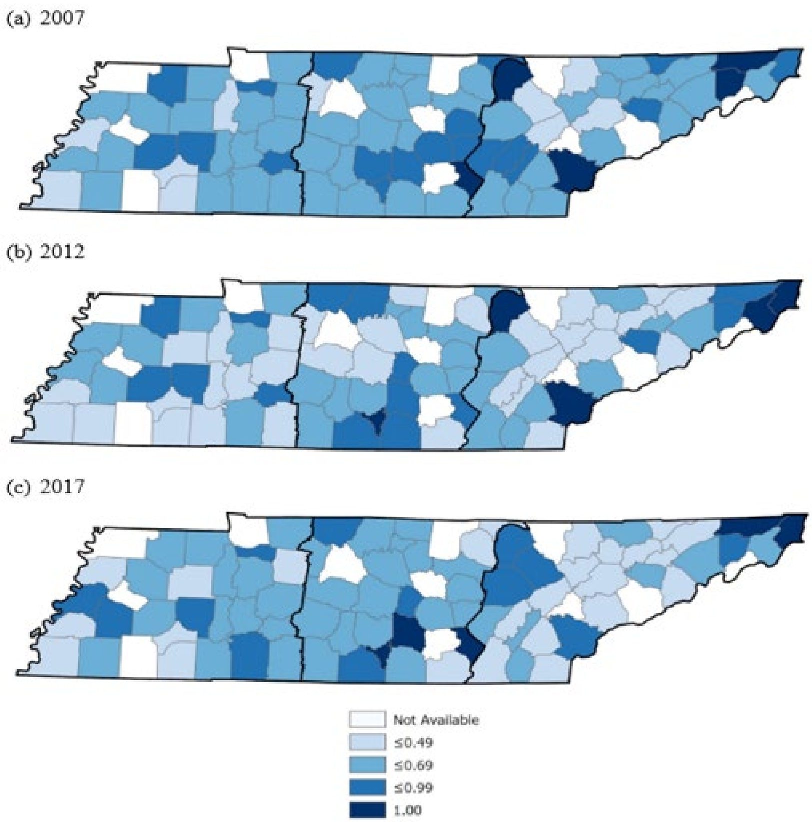

Figure 2. County-Level Technical Efficiency of Beef Production in Tennessee by Year

Table 2 presents county-level average TE scores by region and year. TE decreased in each region and across the entire state from 2007 to 2012 by 10%, but from 2012 to 2017 TE increased 3%. Figure 3 shows a histogram of the TE scores for each of the three years. The distribution of these scores shifted from being more normally distributed in 2007 to being more positively skewed in 2012 and 2017. This is important because it shows the percentage of highly efficient counties did not change across the three years. The percentage of counties with a TE between 0.8 and 0.9 was 5% in 2007, 6% in 2012, and 6% in 2017. Within the TE range of 0.9 to 1, the percentage of counties was 10% in 2007, 11% in 2012, and 9% in 2017. The decline in TE from 2007 to 2012 was primarily due to the counties with TE between 0.5 and 0.7 becoming even more inefficient.

Table 2. Average Technical Efficiency Score for Tennessee Beef Cattle Operations by Region for 2007, 2012, and 2017

Region	2007	2012	2017
East	0.667	0.604	0.592
Central	0.661	0.595	0.641
West	0.605	0.528	0.557
Tennessee	0.647	0.579	0.598

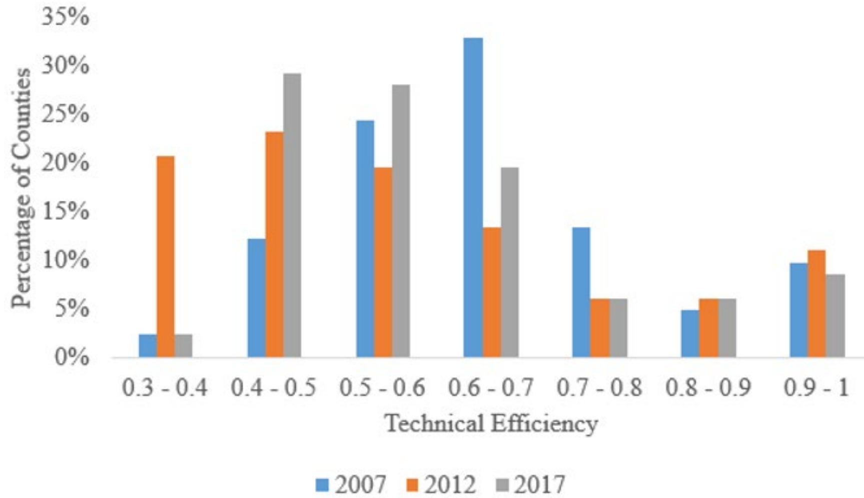

Figure 3. Histogram of the Average County-Level Technical Efficiency of Beef Production in Tennessee by year

Several likely events could explain the decrease in efficiency from 2007 to 2012. During this time, the cattle cycle was in a contractionary period and the number of Tennessee operations that produced and sold beef decreased 17%, and the total number of beef cattle in Tennessee decreased by 13% (USDA NASS, 2019). The average pasture and hay acres per farm in 2007 (66.83 + 46.59 acres) increased by 32 acres in 2012 (91.46 + 54.59 acres) while the average herd size increased by two head (Table 1). Even though pounds per operation increased, the total pounds per pasture and hay acre decreased from 118 pounds per acre (13,420/(66.83 + 46.59)) in 2007 to 106 pounds per acre in 2012 (15,491/(91.46 + 54.59)) (Table 1). These results and data indicate that during this time period, the number of operations decreased faster than the number of cattle, resulting in farms becoming larger but their average herd size remaining fairly constant. This could likely explain the decrease in TE during this time period. Despite having programs like MBP, remaining profitable during the contractionary periods of the cattle cycle is challenging. According to the of Minnesota FINBIN database, cattle producers in nine states (Minnesota, North Dakota, Nebraska, Missouri, Ohio, Michigan, Wisconsin, South Dakota, and Utah) reported negative net returns in 2008, 2009, and 2010 (University of Minnesota, 2019).

From 2012 to 2017, TE increased by 3% across Tennessee. In 2014, the cattle cycle shifted from the contractionary period into an expansion period and producers reported historically high profits in 2014 and 2015 (University of Minnesota, 2019). During this time, operations produced more pounds of cattle and increased average herd size while the average number of pasture and hay acres decreased (Table 1). Thus, the average TE rose from 2012.

Looking at these measurements by region, in 2007 and 2012 the eastern region of Tennessee had the highest average TE followed by the central and western regions. However, in 2017, the central region surpassed the eastern region as the most technically efficient region for beef cattle production in Tennessee. From 2007 to 2012, the central and western regions saw a larger average decrease in TE than the eastern region but, while TE increased 8% in the central region and 5% in the western region from 2012 to 2017, TE decreased by 2% in the eastern region. More research and efforts are needed to better understand what is driving this continued decreased TE in the eastern region. However, this finding is important because it identifies a region that might need additional assistance from Extension to improve efficiency. The relative nature of these measurements also provides insight into how beef producers could learn from peers.

Table 3 shows results from the second-stage regression of region, year, and MBP participation on TE. The year fixed effect indicates that technical efficiency did not vary across years. However, counties in the eastern and central region counties were found to have a higher TE of beef production than counties in the western region. Yet, there was no difference in TE between eastern and central region counties. A negative parameter estimate for MBP shows that increasing MBP participation within a county does improve TE. Obviously, other factors could be driving this, such as the type of producers that are attracted to this program. However, this relationship seems to indicate a positive correlation in program participation and TE within a county. As noted above, using aggregate data such as county-level data to estimate TE has been done but does present challenges.

Table 3. Parameter Estimates from the Maximum Likelihood Truncated Regression of Year, Region, and Master Beef Program Participation on Technical Efficiency

Variables	Parameter Estimates
Intercept	2.056***
MBP	-0.9106**
2007	-0.1517
2012	-0.2907
East	-0.2180**
Central	-0.1654**
Prob > Wald chi-squared	0.0471

***; ** indicate statistical significance at the 0.01 and 0.05 levels
Note: The output dependent variable is the inefficiency index, which is the reciprocal of the TE score. A positive parameter estimate indicates that increasing the independent variable will decrease TE and a negative parameter estimate indicates that increasing the independent variable will increase TE (Simar and Wilson (2007).

Conclusions

This study explored the impacts of the MBP on the TE of Tennessee beef production. We found that, from 2007 to 2012, the TE decreased across the state and for each region. From 2007 to 2012, TE increased statewide but TE still declined in the eastern region. In 2007 and 2012, the eastern region had the highest average TE, but in 2017, the central region was found to have the highest average TE. These results are helpful in identifying where assistance and education could be targeted in the future. Finally, we found a positive relationship in MBP participation and county-level TE of beef production. This program appears to increase TE and could be a model for other states to adopt.

This study is not without limitation. Using county-level data for time periods five years apart is not ideal. Preferably, a survey designed to capture individual producer production data along with economic outputs would improve these results. This would be an interesting area of future research. However, this information does provide useful insight for designing future studies and data collection on regional differences of TE and impacts of MBP.

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