Beyond benchmarks: DEA study of Kansas Farm Productivity.

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Beyond benchmarks: DEA study of Kansas Farm Productivity.

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Abstract

This paper investigates productivity growth as measured by the Malmquist productivity index (MPI) among a sample of 331 Kansas farms between the years 1993 and 2011. The MPI index is decomposed to explore the main sources of productivity growth. Technical change (TC) is found to be the main driver of productivity growth. Previous literature cites relative prices as influential factors affecting technical change and efficiency. Two-way fixed effect regressions of efficiency and productivity measures on relative prices and lagged productivity are conducted. It is shown that past performance is a significant determinant in productivity, while statistical significance of different input and output prices vary. It is suggested that the direction of influence may be the opposite as cited in previous literature, so that past productivity improvements, and associated farm profitability, results in increased input prices.

1 Introduction

Productivity measures the ability of producers to convert inputs into outputs. Productivity growth occurs when more output can be produced with the same level of inputs, the same output can be produced using less inputs, or a combination of the two. In general, productivity growth is linked to competitiveness, economic growth and improved welfare (Lall et al., 2002). In particular, in a context of rapid global population growth, economic expansion coupled with increased environmental concerns and an increasingly more limited ability to expand the extension of the agricultural frontier; agricultural productivity growth is one of the most important factors that will determine food availability and, consequently,
the global ability to fight hunger among other issues. Productivity is closely linked to farm profitability, which at the regional level has significant economic development implications. Arguably, the importance of productivity growth among Kansas farms extend beyond its regional micro-economic relevance.

Agricultural productivity growth has been a feature of postwar United States. Ball et al. (1997) indicate that productivity growth was the principal factor explaining the extraordinary annual agricultural output growth rate of 1.88 percent per year between 1948 and 1994. A well known motto for the state of Kansas is “Kansas farmers feed the world” and thanks to agricultural productivity growth in the state, according to Hallberg (2001), the number of people fed per Kansas farm worker increased from 15.3 in 1950 to 103 in 1998.

Productivity and efficiency are closely related. Improvements in efficiency result, necessarily, in improvements in productivity. However, productivity may also improve “inefficiently” due to technical progress. The relationship between productivity growth, efficiency change, and technical change is explained in the next section. Periodic and interperiodic efficiency scores are calculated to form the different productivity, efficiency change, and technical change scores needed for the analysis. Data Envelopment Analysis (DEA), a nonparametric production frontier estimation method, is used to construct piece-wise linear production surfaces using a sequence of linear programs (one for each period combination for each firm) of which efficiency scores (which are shown to be the inverse of distance functions) are a byproduct.

The remainder of the paper is organized as follows: the next section presents an introduction to DEA, distance functions, productivity and the Malmquist productivity index with a short discussion of the determinants of productivity growth and the empirical models to be estimated. Then, the data are discussed and summarized, including the different productivity and efficiency scores calculated from the DEA procedure. The regression results are then presented and discussed. The final section includes a conclusion
section offering some final thoughts and possible avenues of future research.

2 Methods

This paper measures productivity using the Malmquist index methods described in Färe et al. (1994) and Coelli et al. (1998). The procedure is to construct piece-wise linear production frontiers using Data Envelopment Analysis (DEA) for each year in the data, then calculate different productivity and efficiency scores for each farm for each year using distance functions. Data Envelopment Analysis and the construction of the Malmquist indices are discussed in the next two sub-sections.

2.1 Data Envelopment Analysis and Distance Functions

Data Envelopment Analysis is a technique that uses a series of linear programs to construct piece-wise linear frontiers. Figure 1 illustrates the construction of the production frontier for single input-output technology. Points A, C, D, E, and M represent actual observations. The lines CRS and VRS represent piece-wise linear constant and variable returns to scale technologies, respectively. Notice that farms A, C, D, E define the VRS production frontier and are said to be technically efficient under VRS technology. Only farm C is efficient under CRS technology. Farm M does not lie on the frontier and is said to be technically inefficient. The degree of technical efficiency for each farm is a by-product of the way DEA constructs the production frontier.

In an input oriented DEA setting, such as this, DEA constructs the efficiency frontier by finding the maximum possible reduction in input use that could produce the level of output observed under a given technology. For farm M, DEA will find the proportion $\lambda$ by which input usage can be reduced and still achieve output level $P$. In other words, DEA consists of finding the proportion $\bar{P}B/\bar{P}M$ for the VRS case and the proportion $\bar{P}N/\bar{P}M$ for the CRS case. Notice that the larger the efficiency score, the smaller the distance to the
corresponding frontier, i.e. $M$ is farther away from the CRS frontier than it is to the VRS frontier. This illustrates that technical efficiency scores are a measure of the distance between an observation and a given frontier. The closer the observation to a frontier, the more efficient the farm is. In mathematical terms, let $S$ represent the production technology set, then the relationship between the technical efficiency score $\lambda$ and the distance function for farm $M$, as in Ariyaratne et al. (2006), is defined as:

$$D_M(y, x) = \sup\left[\lambda \in \mathbb{R} : \left(y, \frac{x}{\lambda}\right) \in S\right]$$  \hspace{1cm} (1)

The efficiency scores $\lambda_k$ for each of the $k = 1, 2, ..., K$ farms can be calculated with the linear program below. Assume there are $N$ inputs, $x = (x_1, x_2, ..., x_N)'$, and $M$ outputs, $y = (y_1, y_2, ..., y_M)'$, for each farm $k$ under CRS:
\[
\min_{\lambda^k, z} \lambda^k = D_k^*(y, x)^{-1}
\]

\[\text{s.t.}\]
\[\sum_{k=1}^{K} z_k y_m^k \geq y_m^* \forall m\]
\[\sum_{k=1}^{K} z_k x_n^k \leq \lambda^k x_n^* \forall n\]
\[z_k \geq 0\]

To obtain the efficiency scores under VRS, the constraint \(\sum_k z_k = 1\) is added. There exists a variety of approaches to DEA, for a discussion of DEA methods see Coelli et al. (1998, Ch.6). Efficiency scores and distance functions can be calculated using frontiers from different periods. In general, the inter-period distance function is defined as:

\[
D_{k^*}^r(y^r, x^s) = \sup \left[ \lambda \in \mathbb{R} : \left( y^r_k, \frac{x^s_n}{\lambda} \right) \in S^k \right]
\]

\(D_{k^*}^t(y^r, x^s)\) represents the maximum proportion by which input usage in period \(s\) can be reduced using technology from period \(t\) to produce output levels no less than period \(r\) or, equivalently, the maximal proportional change in input use to make \((y^r, x^s)\) feasible with technology available at time \(t\). Using vector notation, the associated linear program becomes:
\[ \min_{\lambda^{k^*}, z} \lambda^{k^*} = D^t_k(y^r, x^s)^{-1} \]  
\[ \text{s.t.} \]
\[ z'y^t \geq y^r_k \]
\[ z'x^t \leq \lambda^{k^*}x^s_k \]
\[ z > 0 \]

where \( z = (z_1, ..., z_K)' \) is a vector of weights. When \( r = s = t + 1 \) and \((y^r, x^s)\) lies outside the production frontier at time \( t \), \( D^t_k(y^r, x^s) \) represents a change in technology. \( D^t(t) \geq 1 \) so that \( \lambda \leq 1 \) and for technically efficient farms, \( \lambda = 1 \). However, it is possible to observe \( D^t(t + 1) < 1 \) so that \( \lambda > 1 \) if \((y^{t+1}, x^{t+1})\) lies completely outside of production surface \( S^t \).

### 2.2 Productivity, Technical Change and the Malmquist Index

Productivity is the relationship between input use and output production. Given an observed input-output mix, a farm able to produce more output with the same input use or the same output with less input use or both, is said to be more productive than the baseline observation. Productivity changes when the input-output relationship changes because a farm becomes more efficient in converting inputs to outputs (moving closer to the frontier) or because technical change has occurred (shift of the production frontier itself).

The Malmquist Productivity Index (MPI) measures a farm’s change in productivity between two periods by calculating the ratio of the distance between observed input-output combinations in two different periods to a common technology (Coelli and Rao, 2005). The input oriented Malmquist productivity change index between period \( t \) and period \( t + 1 \) can be calculated using technology from either period \( t \) or period \( t + 1 \) as reference (Coelli et al., 1998). When period \( t \) defines the benchmark, as in Caves, Christensen, and Diewert...
(CCD, 1982) the index is calculated as:

\[
M_{it}^{t}(y^t, x^t, y^{t+1}, x^{t+1}) = \frac{D_{it}^{t+1}(y^{t+1}, x^{t+1}) | CRS}{D_{it}^{t}(y^t, x^t) | CRS}
\]

where \(M_{it}^{t}(\cdot)\) compares \((y^t, x^t)\) to \((y^{t+1}, x^{t+1})\) and determines the minimal input inflation factor such that the inflated input for \(t+1: M^t_{i} x^{t+1}\), and period \(t+1\) output, \(y^{t+1}\), lie on the production surface \(S^t\). Conversely, period \(t+1\) may be taken as reference such that the CCD-style index is calculated as:

\[
M_{it}^{t+1}(y^t, x^t, y^{t+1}, x^{t+1}) = \frac{D_{it}^{t+1}(y^{t+1}, x^{t+1}) | CRS}{D_{it}^{t+1}(y^t, x^t) | CRS}
\]

To avoid choosing an arbitrary period benchmark, Färe et al. (1994) suggest a form of the Fisher ideal index so that the Malmquist Productivity Index (MPI) consists of the geometric mean of the indices calculated under the alternative CCD-type benchmarks as explained above:

\[
MPI_i(t, t + 1) = M_{it}^{t}(y^t, x^t, y^{t+1}, x^{t+1}) = \left[M_{it}^{t+1} \times M_{it}^{t}\right]^{\frac{1}{2}}
\]

The above formulation has the added advantage that it can be expanded and decomposed into technical change (TC) and efficiency change (EC) as follows:

\[
MPI_i(t, t + 1) = \underbrace{\frac{D_{it}^{t+1}(y^{t+1}, x^{t+1})}{D_{it}^{t}(y^t, x^t)}}_{EC} \times \underbrace{\left[\frac{D_{it}^{t+1}(y^{t+1}, x^{t+1})}{D_{it}^{t+1}(y^{t+1}, x^{t+1})} \times \frac{D_{it}^{t}(y^t, x^t)}{D_{it}^{t+1}(y^t, x^t)}\right]^{\frac{1}{2}}}_{TC}
\]

Technical Change (TC), as explained before, involves productivity growth due to shifts in the production frontier and it can be further decomposed, following Färe and Grosskopf

\footnote{The benchmark period \(s\) determines to employ \(D^s\) while the period being evaluated \(t\) determined that the correspondent distance for coordinate \((y^t, x^t)\) will go in the denominator. Coelli et al. (1998, Ch.3) has a good introduction to distance functions.}
(1996), into the magnitude of technical change and degree of input (IBI) and output (OBI) bias indices:

\[ TC = \frac{D_i(y^t, x^t)}{D^{t+1}_i(y^t, x^t)} \times \left[ \frac{D^{t+1}_i(y^t, x^{t+1})}{D^{t+1}_i(y^t, x^t)} \right]^{\frac{1}{2}} \times \left[ \frac{D^{t+1}_i(y^t, x^{t+1})}{D^{t+1}_i(y^t, x^{t+1})} \right]^{\frac{1}{2}} \times \left[ \frac{D^{t+1}_i(y^t, x^{t+1})}{D^{t+1}_i(y^t, x^{t+1})} \right]^{\frac{1}{2}} \]  

(9)

The first component is the magnitude of technical change along a ray through the period \( t \) observation. The input bias index for time \( t \) holds the output vector constant at time \( t, y^t \), and compares the magnitude of technical change along a ray through \( x^{t+1} \) with the magnitude of technical change along a ray through \( x^t \). Similarly, the output bias index holds input use constant, \( x^t \), and compares the magnitude of changes of rays along \( y^t \) and \( y^{t+1} \). Output bias indicates that the nature of the technical change is such that the production possibilities frontier has tilted on the output side. Presence of input bias indicate that isoquants have rotated.

All distance functions were calculated using CRS technology. The changes in efficiency can be explained by, and the scores decomposed into, changes in pure technical efficiency (PEC) and changes in scale efficiency (SC). For these efficiency measures, distance functions based on VRS technology are needed as indicated below. Efficiency change (EC) can then be decomposed as follows:

\[ EC = \frac{D^{t+1}_i(y^{t+1}, x^{t+1})}{D_i(y^t, x^t)} \times \frac{D^{t+1}_i(y^{t+1}, x^{t+1})}{D^{t+1}_i(y^{t+1}, x^{t+1})} \times \frac{D^{t+1}_i(y^{t+1}, x^{t+1})}{D^{t+1}_i(y^{t+1}, x^{t+1})} \times \frac{D^{t+1}_i(y^{t+1}, x^{t+1})}{D^{t+1}_i(y^{t+1}, x^{t+1})} \]  

(10)

The set of expansions presented above, allows the Malquist Productivity index as the product of pure technical efficiency change, scale change, magnitude of technical change, input bias and output bias indices.

\[ MPI_i(t, t+1) = PEC(t, t+1) \times SC(t, t+1) \times TC_{mag} \times IBI \times OBI \]  

(11)

A Malmquist productivity index (MPI) of 1 indicates no change in productivity. If an
Figure 2: Example evolution of a set of price indices: *Induced innovation theory suggests that input-saving technical change (in this particular subset of commodities) should occur with respect to seed input use.*

An increase in productivity occurred between $t$ and $t + 1$, then $MPI_i(t, t + 1) > 1$. Conversely, if productivity deteriorated during the same period, this is evidenced by $MPI_i(t, t + 1) < 1$.

### 2.2.1 Determinants of Productivity

Ariyaratne et al. (2006) indicate in their study of agricultural cooperatives that induced innovation theory suggests that technical progress is determined by input and output relative prices. Specifically, increases in relative input prices induce input saving technologies while increases in relative output prices are to focus on the most valuable commodities.

Figure 2 plots the trajectory of Price indices according to USDA’s NASS for prices received, prices paid for chemicals, prices paid for machinery, and prices paid for seeds. Notice that these are price indices with year 2011 as a base, so the convergence towards
that year is not indicative of convergence in prices, just a common base-year. The
important feature in the graph is the slope of the different lines which signal the rate of
increases in prices. According to induced innovation theory, one would expect to see
significant input bias. In the case of the graph, it would indicate technical change leaning
towards seed input saving technologies.

Because the data in this paper are for composite groups of outputs and inputs, a precise
relationship as suggested by the discussion in the previous paragraph is not possible.
However, the theoretical relationships between the different productivity growth
components can be empirically tested. Accordingly, the set of two-way fixed effects
regression models is formulated below to validate the expected relationships.

\[ PEC_{it} = f(p_{it}, w_{it}, MPI_{it-1}) + \theta_i + \eta_t + \epsilon_{it} \]
\[ SC_{it} = f(p_{it}, w_{it}, MPI_{it-1}) + \theta_i + \eta_t + \epsilon_{it} \]
\[ TC_{it} = f(p_{it}, w_{it}, MPI_{it-1}) + \theta_i + \eta_t + \epsilon_{it} \]
\[ MPI_{it} = f(p_{it}, w_{it}, MPI_{it-1}) + \theta_i + \eta_t + \epsilon_{it} \]

where PEC is pure efficiency change, SC is scale efficiency change, TC is technical change,
MPI is the Malmquist productivity index, \( p \) are output prices, and \( w \) are input prices. The
fixed individual and time effects are represented by \( \theta_i \) and \( \eta_t \), respectively, and \( \epsilon_{it} \) is the
error term.

3 Data and Productivity Results

Observations on a balanced panel of 331 Kansas Farm Management Association (KFMA)
farms from year 1993 to 2011 are employed in the analysis. Farms produce two outputs:
crops and livestock, using five inputs: labor, crop input, livestock input, fuel, and other
inputs. More variables are available in the KFMA data bank, for details see Langemeier
Quantities were calculated for each farm considering reported income and expenses by employing output and input price indices from USDA’s Kansas Agricultural Statistics and Agricultural Prices.

Table 1 presents descriptive statistics on the input and output quantities and prices as well as the calculated productivity indicators as explained before. The reported means are for all farms over the period while the standard deviations (S.D.’s) measure the degree of variability as measured by the standard deviation for the whole sample across time and individuals (overall S.D.), variability between different farms (between S.D.), and variability over different periods (within S.D.). Variability is observed over time and across farms for most variables, except for fuel prices and livestock input prices which are the same for all farms in any given period but different over time, i.e. between S.D. is zero.

The sample of farms observed an average of $232,000 per year from crop production with an overall, between, and within standard deviations of $256,000, $199,000, and $156,000, respectively, indicating greater variability in crop income amongst farms than from period to period, the standard deviations for the rest of the variables reported in Table 1 are interpreted similarly. Average livestock income was $66,000 with an average cost of labor, crop input, fuel, livestock input, and other costs of $51,000, $77,000, $20,000, $25,000, and $164,000, respectively. Net farm income was $67,443 on average and showed greater variability from year to year than between individual farms each period as indicated by a between S.D. of $59,797 and a within S.D. of $79,566.

With respect to the productivity indicators, the arithmetic means and between and within standard deviations are also reported in table 1. The arithmetic average annual productivity growth as measured by the Malmquist Productivity Index (MPI) was 7.03 percent over the 19-year period while the geometric mean was 1.12 percent. The MPI ranged from 0.12 to 12.77, however the geometric mean and the median MPI were around 1.01. The use of the geometric mean is preferable to measure longer term trends than the arithmetic mean because the latter tends to overestimate the average when dealing with
strictly positive indicators and can be gravely influenced by outlying observations. The median is the most typical measure of the “center” of the data, which in this case is also more in line with the geometric mean. The arithmetic and geometric means are very similar for the components of the MPI except for Technical Change with an arithmetic mean score of 1.04, i.e. 4 percent average annual progress, a geometric mean of score of 1.01 and median score of 1.019.

The mean for the other components of the decomposed Malmquist productivity index are also included in table 1. This data indicates there was output bias with an average index of 1.034 as opposed to the average input bias index of 0.996 indicating that technical change was biased towards augmenting the level of outputs given input use, i.e. yield improving technical change. On average, there was less change in Pure Efficiency and Scale Efficiency. The median, arithmetic and geometric Pure Efficiency Change (PEC) mean scores were 1, 1.02, 1 and 1, 1.01, 0.99 for Scale Efficiency Change (SC). Annual average Technical Change (TC) occurred at median, mean, and the geometric mean of 2, 4 and 1 percent respectively. Therefore, on average, farms have improved the efficiency given their size as well as changed their size towards the level in which they can observe constant returns to scale.

Data on farms enrolled in the KFMA program are self-selecting. Because these farms are actively seeking improvements in their profitability and productivity, they are more likely to define the production frontiers needed to calculate the different productivity and technical change measures involved in this paper. Furthermore, the regression models presented here and informed by previous literature likely suffer from omitted variable bias (OVB) because the different productivity and efficiency measures are affected by unobserved and unobservable variables, some of which are accounted for by individual and time fixed effects regressions. Because this data was developed in a manner similar to Ariyaratne et al. (2006), the same caveats from the latter apply: because quantities and prices were not observed for each farm, but rather calculated from available price indices,
the data conversion procedures may not accurately represent an individual farm’s inputs and outputs.

To control for the possibility of extreme individual or time events, a two-way fixed effects model is used. In the two-way Fixed Effects (FE) estimation, the time-invariant and individual-invariant variables vanish and only variables that show variation in both dimensions remain. Consequently, because the same prices for fuel and livestock inputs were considered for each year for all farms, these regressors are not used in the two-way FE model. For comparison, an individual FE model is also estimated and the results reported in Table 2.

4 Regression Results

The set of regressions was based on induced innovation theory, which postulates that input and output prices determine technical change by providing incentives to direct research towards the most valuable outputs and scarce inputs. Given exogenous output and input prices, farmers adapt their practices, crop and livestock output portfolio, and the input mix to maximize profits. The market establishes incentives via prices and the farmers make allocation decisions and choose which production technologies to employ. In a sense, technical change and productivity gains are “pulled” by the farmer. Consequently, prices are exogenous and productivity measures endogenous.

The two-way Fixed Effects model allows the use of panel data to identify the effects of different price indices while controlling for farmer individual fixed effects and year fixed effects without needing to impose assumptions about error distribution or use instrumental variables. A set of individual FE regressions is presented for comparison in Table 2. The two-way FE regression results are presented in Table 3. In the case of the Malmquist productivity index (MPI) the Arellano-Bond estimator was employed rather than the typical two-way fixed effects model. The Arellano-Bond estimator was designed to address
the issue of autocorrelation in short panels by selecting appropriate lagged values of the
dependent variable and independent variables as instruments for the lagged dependent
variable.

Notice that the regression results, reported in Table 3, produce a limited number of
significant coefficients when compared to the one way model, which validates the notion
that fixed year effects exist in the data. In the two-way FE models, the lagged MPI has a
negative and significant effect on all measures: PEC, SC, TC, and MPI. This indicates that
after a season with an improvement in productivity, the farm is less likely to see
productivity gains.

Prices do not have a statistically significant effect on Pure Efficiency Change (see table
3). This result is somewhat unexpected and departs from findings in the literature, such as
in Ariyaratne et al. (2006) for agricultural cooperatives, where output prices are found to
be negatively related and input prices positively related to PEC. The intuition in that type
of study is straightforward, ceteris paribus increasing output prices increase the incentive
to over-use inputs in pursuit of increased output while decreasing the incentives to save
inputs by reallocating resources. However, previous findings from different industries were
from OLS regressions that have not accounted for individual or time fixed effects in the
data, thus possibly confounding the effect of prices with one or both of these effects2.

Both, crop input prices and other inputs prices have statistically significant and positive
effects on Scale Efficiency Change (see table 3). As the costs for inputs increase, the
incentive to adjust to reduce average total cost and thus improve the scale efficiency of
production emerges.

Only output prices have a statistically significant, and negative, effect on Technical
Change (see table 3). Increases in the prices of outputs reduce the incentives to migrate to
new technologies as current practices and equipment may continue to be satisfactorily
profitable for the farm. Finally, crop and livestock output prices have significant and

2Ariyaratne et al. (2006) went to great lengths to ensure error terms for each regression model conformed
to the structure required by OLS.
negative effects on MPI while labor and crop input prices have significant and positive effects on MPI. The rationale for the effect of crop and livestock output prices is identical to that provided for TC. The effect of the prices of labor may be explained by the fact that increased wages are typically associated with better, i.e. more productive or able, personnel. Increases in both labor and crop input prices provide incentives to increase productivity to reduce the per unit of output cost of labor and minimize the need to complement production with expensive purchased crops.

5 Conclusions

The productivity of the median Kansas Farm grew at a rate of 1.3 percent per year between 1993 and 2011. The Pure Efficiency Change and the Scale Efficiency Change scores near the center of the data were near 1.00 while the Technical Change scores were between 1.01 and 1.04. These results indicate that the improvements in productivity were driven by technical progress. Productivity growth could also be accelerated by increasing the number of firms producing near the production frontier and right-sizing. Whether this is feasible depends on what the reasons for farms to not be on the frontier are. An econometric analysis of the frontier controlling for individual and time fixed effects may provide some insights into how likely it is for inefficient and “wrong-sized” farms to become more efficient.

Productivity as measured by the Malmquist Productivity Index (MPI) is negatively affected by output price increases and positively affected by input price increases. Lagged MPI score has a negative affect on current productivity. In fact, the lagged MPI score is negative and statistically significant for all of the measures evaluated.

The structure of this inquiry was framed by induced innovation theory, which postulates that input and output prices determine technical change by providing incentives to the most valuable outputs and scarce inputs. Given exogenous output and input prices,
farmers adapt their practices, crop and livestock output portfolio, and the input mix to maximize profits. In this line of thought, the market establishes incentives via prices, the farmer makes allocation decisions and choose which production technologies to employ. In a sense, technical change and productivity gains are “pulled” by the farmer.
### 6 Tables

<table>
<thead>
<tr>
<th>Table 1: Descriptive Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variable</strong></td>
</tr>
<tr>
<td>---------------</td>
</tr>
<tr>
<td>Crop income ($’000)</td>
</tr>
<tr>
<td>Livestock income</td>
</tr>
<tr>
<td>Labor cost</td>
</tr>
<tr>
<td>Crop cost</td>
</tr>
<tr>
<td>Fuel cost</td>
</tr>
<tr>
<td>Livestock cost</td>
</tr>
<tr>
<td>Other costs</td>
</tr>
<tr>
<td>Crop sale price index</td>
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<tr>
<td>Livest sale price</td>
</tr>
<tr>
<td>Labor price ($’000)</td>
</tr>
<tr>
<td>Crop input price index</td>
</tr>
<tr>
<td>Fuel price</td>
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<tr>
<td>Livestock input price</td>
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<tr>
<td>Other prices index</td>
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<tr>
<td>MPI</td>
</tr>
<tr>
<td>Technical chg.</td>
</tr>
<tr>
<td>Input bias</td>
</tr>
<tr>
<td>Output bias</td>
</tr>
<tr>
<td>Bias Index</td>
</tr>
<tr>
<td>Pure Efficiency chg.</td>
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<tr>
<td>Scale Efficiency chg.</td>
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</tbody>
</table>
Table 2: Regression: Fixed individual effects. No control for acreage.

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Model →</th>
<th>PEC</th>
<th>SC</th>
<th>TC</th>
<th>MPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crop price</td>
<td></td>
<td>0.111*</td>
<td>−0.010</td>
<td>−0.862***</td>
<td>−0.873***</td>
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<tr>
<td>Livestock price</td>
<td></td>
<td>0.012</td>
<td>−0.068*</td>
<td>0.009</td>
<td>−0.121</td>
</tr>
<tr>
<td>labor wages</td>
<td></td>
<td>4.35e−7</td>
<td>−1.9e−7</td>
<td>4.3e−7</td>
<td>1.1e−6</td>
</tr>
<tr>
<td>Crop input price</td>
<td></td>
<td>0.037</td>
<td>0.073*</td>
<td>−0.170**</td>
<td>−0.063</td>
</tr>
<tr>
<td>Fuel price</td>
<td></td>
<td>−0.163***</td>
<td>−0.068**</td>
<td>0.625***</td>
<td>0.484***</td>
</tr>
<tr>
<td>Livestock input price</td>
<td></td>
<td>−0.002</td>
<td>0.138*</td>
<td>0.387***</td>
<td>0.621***</td>
</tr>
<tr>
<td>Other prices</td>
<td></td>
<td>0.105*</td>
<td>−0.077*</td>
<td>−0.209***</td>
<td>−0.195*</td>
</tr>
<tr>
<td>Lagged MPI</td>
<td></td>
<td>−0.155***</td>
<td>−0.070***</td>
<td>−0.068***</td>
<td>−0.243***</td>
</tr>
</tbody>
</table>

\[ R^2: \]

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Within</td>
<td>0.08</td>
<td>0.04</td>
<td>0.12</td>
<td>.</td>
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<tr>
<td>Between</td>
<td>0.05</td>
<td>0.14</td>
<td>0.03</td>
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<tr>
<td>Overall</td>
<td>0.07</td>
<td>0.03</td>
<td>0.12</td>
<td>.</td>
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</tbody>
</table>

\[ F(8, 330) = 11.96 \quad 14.37 \quad 191.03 \quad \chi^2(8) = 618.7 \]

*Note: Arellano-Bond regression for MPI.*

Statistical significance indicated at the 1%, 5%, and 10% by (***) , (**) , and (*) , respectively.

Table 3: Regression: Fixed individual and time effects. No control for acreage.

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Model →</th>
<th>PEC</th>
<th>SC</th>
<th>TC</th>
<th>MPI</th>
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</thead>
<tbody>
<tr>
<td>Crop price</td>
<td></td>
<td>−0.125</td>
<td>0.031</td>
<td>−0.277**</td>
<td>−0.956***</td>
</tr>
<tr>
<td>Livestock price</td>
<td></td>
<td>0.055</td>
<td>−0.034</td>
<td>−0.103**</td>
<td>−0.340**</td>
</tr>
<tr>
<td>labor wages</td>
<td></td>
<td>4.28e−7</td>
<td>1.11e−7</td>
<td>5.04e−7</td>
<td>2.6e−6***</td>
</tr>
<tr>
<td>Crop input price</td>
<td></td>
<td>0.007</td>
<td>0.047*</td>
<td>0.141</td>
<td>0.637***</td>
</tr>
<tr>
<td>Fuel price</td>
<td></td>
<td>omitted</td>
<td>omitted</td>
<td>omitted</td>
<td>omitted</td>
</tr>
<tr>
<td>Livestock input price</td>
<td></td>
<td>omitted</td>
<td>omitted</td>
<td>omitted</td>
<td>omitted</td>
</tr>
<tr>
<td>Other prices</td>
<td></td>
<td>0.137</td>
<td>0.498*</td>
<td>−0.222</td>
<td>0.111</td>
</tr>
<tr>
<td>Lagged MPI</td>
<td></td>
<td>−0.183***</td>
<td>−0.095***</td>
<td>−0.038***</td>
<td>−0.288***</td>
</tr>
</tbody>
</table>

\[ R^2: \]

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
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<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Within</td>
<td>0.12</td>
<td>0.09</td>
<td>0.47</td>
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<tr>
<td>Between</td>
<td>0.04</td>
<td>0.18</td>
<td>0.13</td>
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</tr>
<tr>
<td>Overall</td>
<td>0.11</td>
<td>0.08</td>
<td>0.46</td>
<td>.</td>
<td></td>
</tr>
</tbody>
</table>

\[ F(22, 330) = 9.94 \quad 13.05 \quad 504.54 \quad \chi^2(22) = 2330.96 \]

*Note: Arellano-Bond regression for MPI.*

Statistical significance indicated at the 1%, 5%, and 10% by (***) , (**) , and (*) , respectively.
References


