An Analysis of Strategy Shifts Among Kansas Crop Farmers

Nicholas Pates

1 Introduction

The goal of this paper is to find the factors that influence farm productivity changes over time. The UN estimates that population growth rate has been stable, yet exponential rate at around 1.20% from 1990 to 2010 (Gonzalo and Alfonseca, 2016). To support population growth, agricultural productivity needs to consistently improve over time. The extent that changes in technology corresponds to observed productivity growth depends on how responsive farmers are to changes in technology. It is therefore important to understand the incentives and constraints that farmers face as their production sets change.

Since the 1980s, data envelopment analysis (DEA) has become a popular method of studying farm productivity. The DEA approach has some appealing features relative to parametric approaches. They relax assumptions of profit maximization, do not require a specific functional form of the production function, and are easier to estimate relative to flexible functional form model such as Almost Ideal Models (AIMs). DEAs are not without downsides however. In addition, researchers need must be careful when analyzing results of DEAs as they use a somewhat simplistic method of benchmarking farmers against one another. Over time, DEAs have benefited from new research on the approach. I employ a method from Chen and Ali (2004) who convert efficiency measures from the study into binary variables to study what they term as "strategy shifts" over time. This method, adds important context to studying technical change over time using the DEA approach and focuses on relative factor-use which is more in line with the technological change literature.

Productivity is influenced by both exogenous factors such as weather and endogenous factors such as production practices on the farm. At the farm-level, technology availability can be considered an exogenous factor as most do not directly develop the technology that they use. For instance productivity differences between oil-seed and non-oil crops, can be explained by innovations in oil-seed crop production (Wang et al., 2015). However, technology *adoption* is often considered an endogenous decision.

Some researchers have attributed weather variability as one mechanism that drives diffusion of new technology. For instance, Sutch (2011) attributed an especially damaging drought in 1938 as the major event led to the mainstream adoption of hybrid varieties of corn. While there was evidence that hybrid varieties produced higher average yields, Sutch concluded that it was the drought resistance of hybrid varieties that led to farmers paying for the considerably more expensive hybrid seed varieties.

To study technical change in farmers I use a balanced panel of farm-level data from the Kansas Farm Management Association (KFMA) of 450 farmers from 2002 to 2012. The first goal of the analysis is to measure productivity changes. The second goal is to identify farm-level characteristics that are correlated with favorable production decisions over time. A nonparametric measure of productivity growth called a Malmquist Index, a dynamic extension of a DEA is used to benchmark productivity improvements through time. Following Chen and Ali (2004), the frontier shift term of the Malmquist index is used to detect "strategy shifts" among farmers in each year. These strategy shifts can be used to assess the favorability of observed input ratio changes from year to year and provides necessary conditions of technical progress. These strategy shifts, reveal what influences technical change and whether farmers are truly changing their production plans. In the second stage of the analysis, I include the results from the productivity analysis in a multinomial regression model over strategy shifts to show the relationship between technically progressive input choices, exogenous factors, and farm characteristics.

2 A Summary of DEA Analysis and Productivity Change Over Time

DEA is based on linear programming to benchmark producers (commonly referred to as decision making units (DMUs)) relative to other the producers in the sample. DEA obtains these benchmarks by creating convex hull (referred to as a frontier), that "envelopes" the observed input-output data. This method was first introduced by Charnes, Cooper, and Rhodes (1978) and became a method of benchmarking producers of multiple outputs that use multiple inputs. The input-oriented version with constant returns to scale (CRS) is called the Charnes, Cooper, and Rhodes (CCR) model. In this model, a farmer (farmer 0) seeks to reduce its input vector (x_0) as much as possible while still maintaining its observed level of output (y_0). Farmer 0 seeks to find a scalar reduction in its input vector, formally written: $\theta_0 = \min_\theta [\theta \mid \theta x_0 \in F(y_0)]$. Here $F(\cdot)$ represents the feasibility set where $F(y) = [x \mid x \text{ can produce } y]$. When θ_0 is equal to one, farmer 0 is called *efficient*. In this case, the input vector of farmer 0 (x_0) cannot be scaled down while still maintaining production of its observed output (y_0). When θ_0 is less than one, it indicates that farmer 0 is *inefficient* because it could scale down the use of inputs by $\theta_0 < 1$ while maintaining y_0 output.

Since any observed input-output decisions are by definition feasible, the feasible set $F(\cdot)$ is determined by the actions of farmers in the sample. Equation (1) shows the CCR problem for farmer 0 using M inputs and producing S outputs benchmarked against N farmers including farmer 0:

$$\min_{\theta_0, \lambda_{j:j=1,\dots N}} \theta_0 \tag{1}$$

$$s.t.$$

$$\sum_{j=1}^{N} \lambda_j x_{j,i} \leqslant \theta_0 x_{0,i} \ : \ i = 1, \dots, M$$

$$y_{0,k} \leqslant \sum_{j=1}^{N} \lambda_j y_j \ : \ k = 1, \dots, S$$

$$\lambda_j \geqslant 0 \ : j = 1, \dots, N$$

In this problem, farmer 0 adjusts its input vector by a scalar (θ) by benchmarking itself against a composite output and input vector created using observations of the other farmers in the sample. Constant returns to scale is assumed under the CCR model. This means that conic combinations of the observed production plans of the farmers in the sample are considered feasible. To ensure that $\theta_0 x_0 \in F(y_0)$, the scaled input is required to be at least as large as the composite input vector, and the output vector y_0 is restricted to be no greater than the composite output vector[1]. The composite input-output vector is represented as the product of a $N \times 1$ vector (λ) times the respective observed inputs and outputs from the

[1]This follows from free disposal. If $x_1 \in F(y)$ and $x_2 \geqslant x_1$ then $x_2 \in F(y)$. If $x \in F(y_1)$ and $y_1 \geqslant y_2$ then $x \in F(y_2)$.

farmers in the sample. The λ weights are chosen to make farmer 0 as efficient as possible while remaining feasible. Provided that $x \geqslant 0$ for every farmer in the sample, the constraints of the problem will ensure that $0 < \theta_0 \leqslant 1$. If θ_0 is not greater than 0, then the second constraint in program (1) would be violated. The θ_0 term also cannot be above 1. If $\theta_0 > 1$, then λ could be selected so that only $\lambda_0 = 1$ and $\lambda_i = 0 \; \forall i \neq 0$ to reduce the value of θ_0 while conforming to the constraints. The key to this restriction in θ_0 is that farmer 0 is being benchmarked against its own production plan and that the linear program is *minimizing* θ_0.

The model described above is static in the sense that it compares farmer 0 against other farmers in a single period of time. Without the use of DEA techniques Caves, Christensen, and Diewert (1982) describe θ as a productivity "distance" and provide an analytical definition that enabled discrete productivity comparisons between firms with different technologies and between the same firm over time (Caves, Christensen, and Diewert, 1982). The distance term, $D^j(x, y)$ is the proportion of the input vector x that could produce y observed in a particular year, efficiently with period j's technology. Formally, $D^j(x, y) = \min_\theta \left[\theta \mid \theta x \in F^j(y)\right]$. The feasible set in this problem $F^j(\cdot)$ is dynamically defined so that $F^j(y) = [x \mid x \text{ can produce } y \text{ in period } j]$. This study will compare the same farm over different periods in time.

The own-year distance function of farmer 0 is:

$$D_0^t\left(x_0^t, y_0^t\right) = \min_{\theta_0, \lambda_{j:j=1,\ldots N}} \theta_0 \tag{2}$$

$$s.t.$$

$$\sum_{j=1}^{N} \lambda_j x_{j,i}^t \leqslant \theta_0 x_{0,i}^t \;:\; i = 1, \ldots, M$$

$$y_{0,k}^t \leqslant \sum_{j=1}^{N} \lambda_j y_j^t \;:\; k = 1, \ldots, S$$

$$\lambda_j \geqslant 0 \;: j = 1, \ldots, N$$

Cross-year distance functions are defined as:

$$D_0^{t+1}\left(x_0^t, y_0^t\right) = \min_{\theta_0, \lambda_{j:j=1,\ldots N}} \theta_0 \tag{3}$$

$$s.t.$$

$$\sum_{j=1}^{N} \lambda_j x_{j,i}^{t+1} \leqslant \theta_0 x_{0,i}^t \;\; : \;\; i = 1, \ldots, M$$

$$y_{0,k}^t \leqslant \sum_{j=1}^{N} \lambda_j y_j^{t+1} \;\; : \;\; k = 1, \ldots, S$$

$$\lambda_j \geqslant 0 \;\; : j = 1, \ldots, N$$

and

$$D_0^{t}\left(x_0^{t+1}, y_0^{t+1}\right) = \min_{\theta_0, \lambda_{j:j=1,\ldots N}} \theta_0 \tag{4}$$

$$s.t.$$

$$\sum_{j=1}^{N} \lambda_j x_{j,i}^{t} \leqslant \theta_0 x_{0,i}^{t+1} \;\; : \;\; i = 1, \ldots, M$$

$$y_{0,k}^{t+1} \leqslant \sum_{j=1}^{N} \lambda_j y_j^{t} \;\; : \;\; k = 1, \ldots, S$$

$$\lambda_j \geqslant 0 \;\; : j = 1, \ldots, N$$

Unlike the own-year distance functions, the composite production plan farmer 0 is not being benchmarked against does not contain its own observed production plan in the cross-period analysis. Therefore the cross-period distance functions can be greater than one. The cross-period distance function $D^{t+1}\left(x^t, y^t\right)$ is the proportional change in the input vector x^t that would allow the firm to efficiently produce at least y^t in output under period $t+1$'s technology. If the technology had regressed in the sense that it would take more than x^t to efficiently produce y^t in period $t+1$, then $D^{t+1}\left(x^t, y^t\right) > 1$. The second cross-period distance function $D^t\left(x^{t+1}, y^{t+1}\right)$ can be interpreted as the proportional change in the input vector x^{t+1} that would allow the farm to efficiently produce at least y^{t+1} in output under period t's technology. If technology *progressed* over from t to $t+1$, then $D^t\left(x^{t+1}, y^{t+1}\right) > 1$ because under t's technology, producing y^{t+1} would have required *more* than x^{t+1} in inputs.

The calculation of these distances and the subsequent Malmquist index were incorporated into the DEA framework by Färe et al. (1992). They applied this method by calculating productivity changes of industrialized countries over time (Färe et al., 1992). They describe the Malmquist Index as a geometric average of distance function ratios:

$$M^t = \frac{D_0^t\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^t\left(x_0^t, y_0^t\right)} \text{ and } \tag{5}$$

$$M^{t+1} = \frac{D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^{t+1}\left(x_0^t, y_0^t\right)}\ . \tag{6}$$

If M^t is greater than one, then the production plan $\left(x_0^{t+1}, y_0^{t+1}\right)$ is less efficient at time period t than the firm's past production plan (x_0^t, y_0^t). If M^{t+1} is greater than one, then the production plan $\left(x_0^{t+1}, y_0^{t+1}\right)$ is relatively more efficient in period $t+1$ than (x_0^t, y_0^t) would have been. The geometric average of M^{t+1} and M^t gives the *Malmquist Index* between periods t and $t+1$ for farmer 0.

$$M = \left[\frac{D_0^t\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^t\left(x_0^t, y_0^t\right)} \frac{D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^{t+1}\left(x_0^t, y_0^t\right)}\right]^{\frac{1}{2}} \tag{7}$$

To aid interpretation, the Malmquist Index is often represented as a product of a technical efficiency component and a frontier shift component. To obtain this form, equation (7) is multiplied and divided by $\frac{D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^t\left(x_0^t, y_0^t\right)}^{\frac{1}{2}}$.

$$M = \frac{D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^t\left(x_0^t, y_0^t\right)} \left[\frac{D_0^t\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)} \frac{D_0^t\left(x_0^t, y_0^t\right)}{D_0^{t+1}\left(x_0^t, y_0^t\right)}\right]^{\frac{1}{2}} \tag{8}$$

This form of the Malmquist Index decomposes the sources of the productivity change. Chen and Ali (2004) call the first term $\left(\frac{D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^t\left(x_0^t, y_0^t\right)}\right)$ the *technical efficiency change* (TEC) from period t to $t+1$ and the second term $\left[\frac{D_0^t\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)} \frac{D_0^t\left(x_0^t, y_0^t\right)}{D_0^{t+1}\left(x_0^t, y_0^t\right)}\right]^{\frac{1}{2}}$ the *frontier shift* (FS) term. When the technical efficiency change term is above one, farmer 0 was closer to the own-year efficient frontier in period $t+1$ that it was in period t. While the technical efficiency change term tells how close farmer 0 is to the own-year frontier, it does provide enough information to confirm that farmer 0 improved its productivity from one year to the next as the frontier itself is subject to change over time. The frontier shift term captures the average distance between the frontiers from two different years evaluated at the output levels for each respective year. When frontier shift term is above one (below one), technology, has progressed (regressed) from period t to $t+1$.

While the technical efficiency change and frontier shift terms are important components, Chen and Ali (2004) point out that more information can be obtained from the two components within the geometric average of the frontier shift term. These terms are:

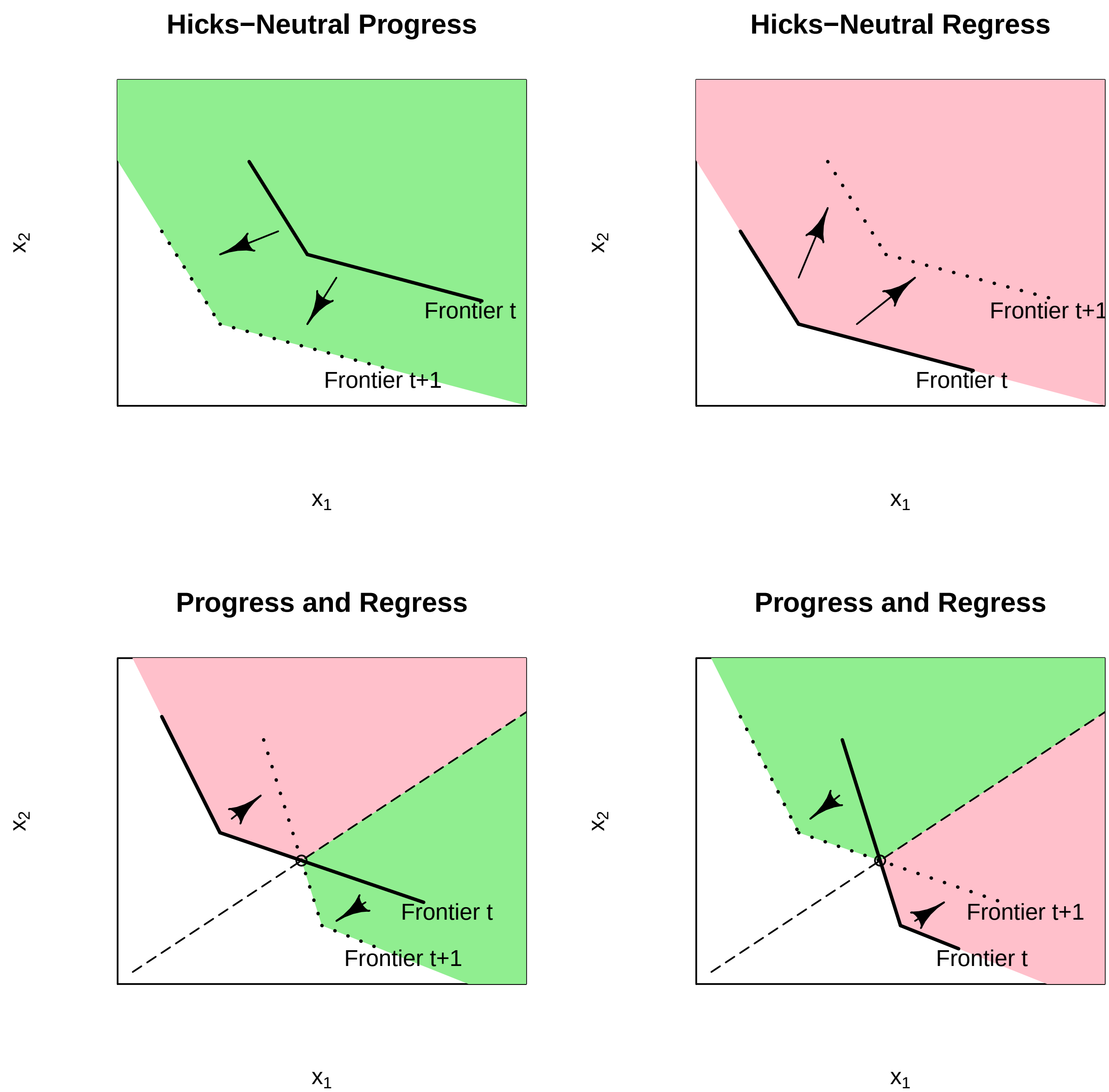
$$FS_1 = \frac{D_0^t\left(x_0^t, y_0^t\right)}{D_0^{t+1}\left(x_0^t, y_0^t\right)} \tag{9}$$

$$FS_2 = \frac{D_0^t\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)} \tag{10}$$

These two components represent the ratios of radial distances between the efficient isoquants in t and $t+1$ $\left(\frac{Radial\ Distance\ of\ t\ Frontier}{Radial\ Distance\ of\ t+1\ Frontier}\right)$. Technical improvement occurs when isoquant frontier moves closer to the origin over time. Therefore, when these terms are above one, this means that the period t frontier is further away from the origin than the period $t+1$ frontier, indicating technical improvement. The components of the frontier shift term represent these ratios of distances, evaluated from different production plans. The FS_1 term is the distance between the frontiers evaluated at the period t production plan and the FS_2 term is the distance ratio evaluated at the production plan observed in $t+1$.

Using the frontier shift terms, input space can be partitioned into areas of technical progress and regress. Figure (1) shows the four possible ways that productivity of input ratios can change over time. The top left panel describes a Hicks-Neutral technical progress. Under this change, every input ratio becomes relative more productive over time. The top right panel shows Hicks-Neutral technical regression where every input ratio becomes less technically efficient. The bottom two panels show a mixture between the two, where the isoquants cross. This means that certain input ratios become relatively more efficient and others become relatively less efficient.

Figure 1: Hicks-Neutral Technical Regress



Using the intuition from figure (1) the frontier shift components can describe farmer's input decisions using four strategy shift types.

$$\text{Positive to Positive (PP): } [FS_1 > 1 \ , \quad FS_2 > 1] \tag{11}$$

$$\text{Negative to Negative (NN): } [FS_1 < 1 \ , \quad FS_2 < 1] \tag{12}$$

$$\text{Negative to Positive (NP): } [FS_1 < 1 \ , \quad FS_2 > 1] \tag{13}$$

$$\text{Positive to Negative (PN): } [FS_1 > 1 \ , \quad FS_2 < 1] \tag{14}$$

When $FS_1 > 1$, farm 0's older production plan (x_0^t, y_0^t) was in an area of technical progression (the green areas in figure (1)). $FS_2 > 1$ indicates that the farm's new production plan $\left(x_0^{t+1}, y_0^{t+1}\right)$ is in an area of technical progress. Since FS is simply a geometric average of FS_1 and FS_2, when FS_1 and FS_2 are both greater than one, then FS will be greater than one, indicating technical progress. Conversely when FS_1 and FS_2 are less than one, then FS will be less than one indicating technical regress. However, when $FS_i > 1$ and $FS_j < 1$ where $i \neq j$, the value of the frontier shift term is ambiguous. Put simply, the value of the strategy terms will depend on *where the frontier distances are evaluated.* Chen and Ali (2004) further point out that the Malmquist Index, looked at on its own, may omit important context that affects the production growth outlook for firms.

When one thinks of technical progress, one implicitly views the efficiency earlier differently from efficiency later on. Progress is seen as an advance in technology as time moves forward. If in a previous period, a farmer experienced a optimal weather conditions Since the Malmquist Index averages the individual frontier shift components together, one could claim technical progress if the earlier frontier shift term F_1 were large enough. In extreme cases, this result could arise regardless of whether F_2 were less than one or not. Because of this fact, the Malmquist Index may not truly represent progress as it is normally understood. The implications that follow from the functional form of the Malmquist Index imply that one has to be careful about interpreting the Malmquist Index.

Figure (2) graphically illustrates the four strategy shifts. Suppose that between periods t and $t+1$, the industry experienced a factor biased technical change where input x_1 became relatively more productive (x_2 became relatively less productive). This type of technical change will produce a point at which the two isoquants cross. I draw a line from the origin to the isoquant intersection point. On one side of this line I see technical *progression*, as producing a given output requires less x_1. On the other side of the line, technology has *regressed* as it requires more x_2 to produce a given level of output. Careful examination of the components of the frontier shift reveal that I can characterize strategy shifts by the locations of the farm's production plans with respect to this line.

In period t suppose the farm has two potential production plans (P_t^1 and P_t^2). It is clear that P_t^1 is an area of technical progress and P_t^2 is in an area of technical regress. In period $t+1$, industry experiences technical change biased towards x_1. I again assume that the farm has two potential production plans P_{t+1}^1 and P_{t+1}^2. Notice that P_{t+1}^1 lies to the left of the period t isoquant while P_{t+2}^2 lies to the right. I can therefore say that the farm technically progresses if it chooses P_{t+1}^1, and will regress if it chooses P_{t+1}^2. From here, I can define our strategy shifts. A farm with the production plans $\left(P_t^1, P_{t+1}^1\right)$ made a positive to positive strategy shift. A farm with the production plans $\left(P_t^2, P_{t+1}^2\right)$ made a negative to negative strategy shift. However, if the farm's production plan moves from one side of the ray to the other, the farm will move from a positive to a negative $\left(P_t^1, P_{t+1}^2\right)$ or a negative to positive $\left(P_t^2, P_{t+1}^1\right)$ strategy shift. Although a farm with plans $\left(P_t^2, P_{t+1}^1\right)$ has improved technologically, $FS < 1$ is still a possibility since it will evaluate the geometric averages frontier distances. A similar argument can be made in the other direction if a farmer has production plans $\left(P_t^1, P_{t+1}^2\right)$.

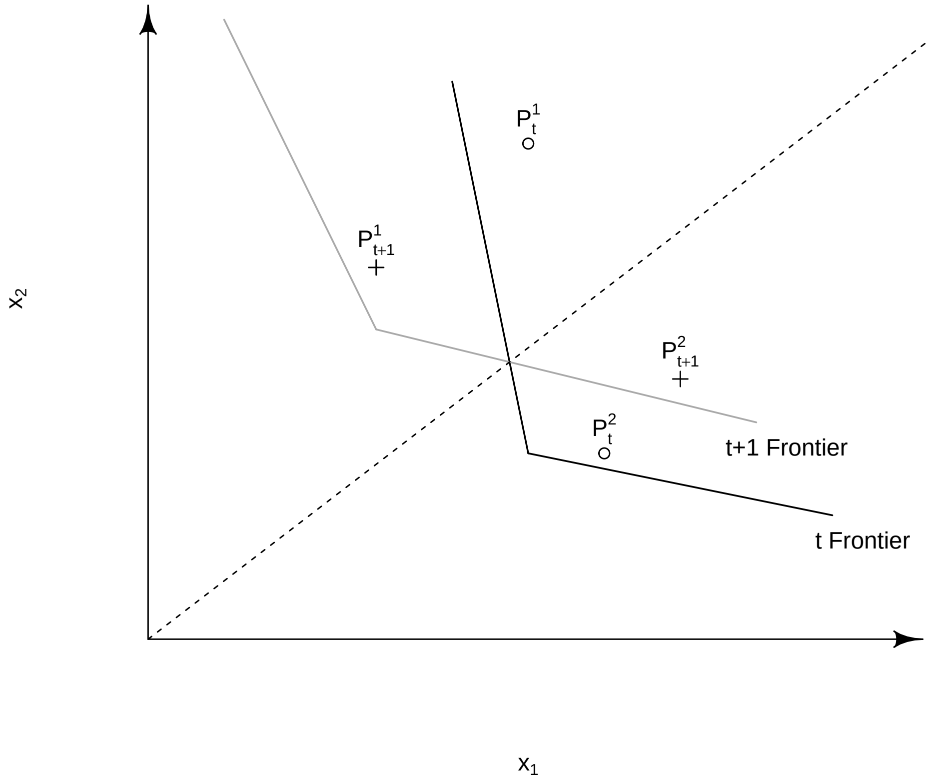


Figure 2: Strategy Shifts When Shifting Isoquants Cross

In order to understand the analysis in the next sections it is also helpful to know what the values of these frontier components represent. Consider figure (3) which is identical to figure (2) with only feasible plans for *both* periods and rays to these plans from the origin. Suppose that a farmer remains at one of these two points during both periods. Calculating the frontier shift terms, if the farmer produces at P_t^1 in both periods then,

$$FS_1\left(P_t^1\right) = \frac{D^t\left(x^t\right)}{D^{t+1}\left(x^t\right)} = \frac{\frac{OA}{OP_t^1}}{\frac{OB}{OP_t^1}} = \frac{OA}{OB} > 1 \tag{15}$$

$$FS_2\left(P_t^1\right) = \frac{D^t\left(x^{t+1}\right)}{D^{t+1}\left(x^{t+1}\right)} = \frac{\frac{OA}{OP_t^1}}{\frac{OB}{OP_t^1}} = \frac{OA}{OB} > 1 \tag{16}$$

$$FS\left(P_t^1\right) = \left[\frac{OA^2}{OB^2}\right]^{\frac{1}{2}} = \frac{OA}{OB} > 1 \tag{17}$$

Conversely if the P_{t+1}^2 is used in both periods, then the frontier components will be:

$$FS_1\left(P_{t+1}^2\right) = \frac{D^t\left(x^t\right)}{D^{t+1}\left(x^t\right)} = \frac{\frac{OD}{OP_{t+1}^2}}{\frac{OC}{OP_{t+1}^2}} = \frac{OD}{OC} < 1 \tag{18}$$

$$FS_2\left(P_{t+1}^2\right) = \frac{D^t\left(x^{t+1}\right)}{D^{t+1}\left(x^{t+1}\right)} = \frac{\frac{OD}{OP_{t+1}^2}}{\frac{OC}{OP_{t+1}^2}} = \frac{OD}{OC} < 1 \tag{19}$$

$$FS\left(P_{t+1}^2\right) = \left[\frac{OD^2}{OC^2}\right]^{\frac{1}{2}} = \frac{OD}{OC} < 1 \tag{20}$$

This illustrates that if a farm uses the same inputs in two consecutive periods, then the farm will have a PP or NN shift. Only when I observe movements over dashed line will I see NP or PN shifts. It also illustrates that when I have factor neutral technical progress (regress), there will not be a point where the isoquants cross and I will only observe PP (NN) shifts.

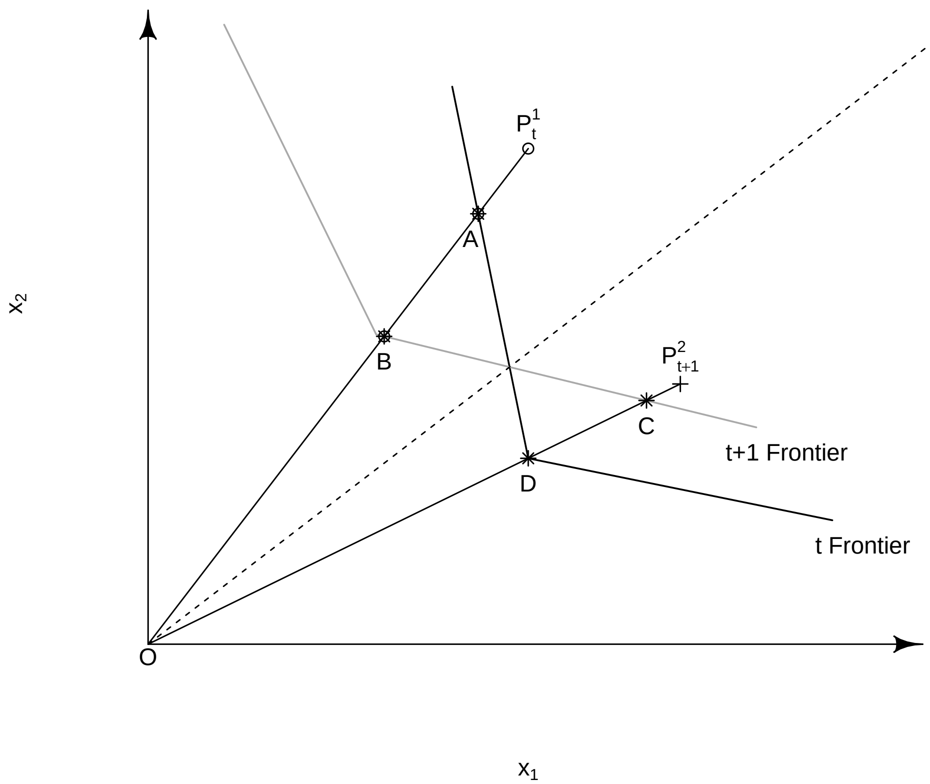


Figure 3: Strategy Shifts When Production Plans Do Not Change

3 Data

This study uses farm-level data from the Kansas Farm Management Association (KFMA) database. I consider farmers in the dataset that were continuously observed from 2002 to 2012. These years were selected to produce a sufficiently large panel and because county-level weather data were available through 2012. These data include only farmers that designate themselves as primarily crop producers. I do not include livestock producers in this sample as the analysis of Wang et al. (2015) suggests that the effect that weather has on productivity of crop producers is different from the effects on livestock producers. The panel data observes the production choices of 450 crop producers over the course of 11 years. The KFMA data were also used to provide farm characteristics.

Since this analysis studies the favorability of decisions, I include the age of the primary operator in the second stage of the analysis. Age can indicate many things about a farmer. Age could be proxy for farmer experience. Farmers with more experience may be more aware of potential adjustments from year-to-year and may positively influence the likelihood of favorable input changes. However, older farmers may be less educated relative to younger cohorts or may be less adept at picking up the latest technology (Coelli and Battese, 1996; Mishra et al., 2009).

Soil quality of the farm also a potentially important variable to include. Farms with higher soil quality may not need to apply as much fertilizer or other chemicals to substitute for inferior soil quality. Unfortunately, the KFMA dataset only identifies farmers at the county level and within counties, soil quality may be highly heterogeneous. I control for soil characteristics somewhat by the location of farms. In the state of Kansas, North-South geography can proxy for soil quality.

Other important farm characteristics include its relative size, crop diversity, and crop intensity. To measure relative size, I use a size (crop) index which is equal to:

$$CI_{it} = \frac{A_{it}}{max_i\,(A_{it})} \tag{21}$$

Where A_{it} is farmer i's total acreage at time t. To measure the level of crop intensity, I divide the total crop acreage for each farm by the crops total operated acreage which includes land-used for pasture, forage and other uses. This gives an idea of how focused the farmer is on crop production as well as an indication for flexibility in farm-land use for crop production. Crop diversity may also be important, measure of individual crop intensity. Farms with a higher level of crop diversity may not be able to take full advantage of crop technology in a particular year and may not be as nimble when conditions change. However, if the farm's crop profile is more diverse, it may be more robust to changes in the weather. Additionally, farmers with a more diverse crop portfolio may also retain higher levels of soil nutrients from year-to-year, leaving the option to fertilize less during adverse weather events. Following Coble et al. (1996), I compute each farm's crop-share Herfindahl index, this index is equal to:

$$HI_{it} = \sum_{c=1}^{C} \left(\frac{A_{cit}}{\sum_{c=1}^{C} A_{cit}} \right)^2 \tag{22}$$

Where A_{cit} is the acreage farmer i dedicates to crop c in year t. If a farm grows a single crop then $A_{cit} = \sum_{c=1}^{C} A_{cit}$ and its Herfindahl index would equal one. If the farmer grew two crops with equal acreage shares, then $HI_{it} = (0.5)^2 + (0.5)^2 = 0.5$. The more diverse the crop profile, the lower the Herfindahl index.

Financial stress is included to measure of farm's leverage with the debt-to-asset ratio. The KFMA dataset contains information on the total debt and total value of farm assets (Langemeier, 2003). The ratio of these terms serves as an indicator of the farm's financial stress. Giannakas, Schoney, and Tzouvelekas found a positive relationship between a farmer's debt-to-ratio and technical efficiency. They conclude that farmers carrying higher debt are doing so to finance expansions and farm improvements (Giannakas, Schoney, and Tzouvelekas, 2001). In another study, Sotnikov found that short and long-term debt hindered technical growth (Sotnikov, 1998).

Wang et al. compares the productivity growth between crop and livestock enterprises noting that the total factor productivity growth for crop producers was significantly higher growth rate but was also more variable year-to-year. They suggest that the growth of productivity of crop producers is sensitive to weather (Wang et al., 2015). To account for weather, the second stage model will incorporate county-level annual degree-growing days with a 10°C baseline, and estimated soil moisture content. These statistics were estimated from the PRISM Climate Group (PRI, 2016).

For most datasets, simpler DEA models generally provide better insights than more complex ones due to curse of dimensionality. For this reason, the DEA is set up with a single output and four inputs. Since the prices of each of the major crops are correlated over the years in this analysis, the DEA considers production total value of farm production (TVP) as its output. Farmers use labor (total number of full-time equivalent laborers including the primary operator), land (total crop acreage), machinery (total crop machinery investment plus total crop machinery cost), and other inputs (total fertilizer cost, seed expenses, irrigation energy expenses, crop marketing and storage expenses, herbicide and insecticide expenses, building repairs, cash farm rent expenses, utility expenses, and crop insurance expenses). These variables are available through the KFMA database and are described in detail in the database's documentation (Langemeier, 2003).

Because much of the data that enter the DEA are in dollar terms and the analysis occurs over time, they were normalized using national price indices for inputs and outputs provided by the Farm Service Agency (FSA) via the USDA's QuickStats. Figure (4) shows the number of farms in the sample by each county in Kansas. The sample covers most of the major portions of Kansas but there are a particularly high number of farmers in the central and eastern parts of the states and fewer farmers from the southwestern portion of the state.

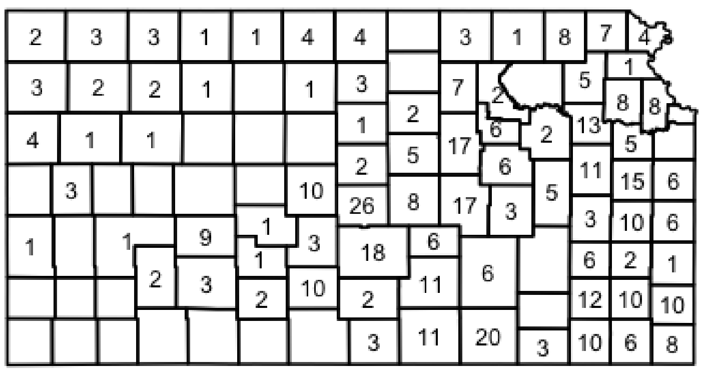


Figure 4: Number of Sampled Farms by County

Table (1) shows the mean values for our output and inputs for each year. Values in dollar figures were normalized using price indices from QuickStats. Overall the value of total farm production (TVFP) generally increased at an average rate of 6.73% per year. There was a negative shock to TVFP starting in 2005 lasting until 2008 which rebounded in 2010. Data from the Risk Management Agency's Cause of Loss (COL) report shows that Kansas farmers experience higher non-price related payouts per acre in insurance over this period, especially in 2011. Total crop acres however grew rather steadily at a rate of about 1.64%. Over our time period, labor use decreased slightly but overall did not change very much. Machinery expenses grew at an average of 1.55% per year but had significant increases after 2007 growing at an average annual rate of 6%. The most interesting changes came from the "Other" category. These expenses, on average, grew at a higher rate (4.18%) than machinery expenses.

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Total Crop Acres	1384.67	1408.94	1423.38	1459.27	1480.63	1502.2	1543.12	1554.48	1584.75	1613.68	1639.29
Acres Operated Total	1725.32	1754.88	1724.47	1752.49	1810.02	1805.32	1866.47	1859.7	1887.44	1917.68	1938.1
Other Expenditures	1826.6	1922.8	1935.12	2090.1	2016.6	2146.02	2040.24	2210.2	2313.12	2409.81	2659.38
Machine Expenditures	4763.63	4542.49	4472.75	4257.37	4142.15	4098.16	4134.1	5075.57	5308.56	5224.57	5561.34
Total Value of Farm Production	3548.5	3970.84	3872.65	4207.98	4438.01	4959.09	5746.21	6144.1	6094.66	5798.9	6190.02
Labor (Full-Time Workers)	1.37	1.38	1.38	1.36	1.35	1.31	1.35	1.34	1.36	1.33	1.33

Table 1: Sample Summary Statistics

4 Analysis With The Malmquist Index

The purpose of this analysis is to determine the characteristics of farmers that experience technical improvements over time. To do this, I use an input-oriented the constant returns to scale version of the Malmquist Index. I start by calculating the Malmquist index on all farms to obtain their distance functions: $\frac{D^{t+1}\left(x^{t+1},y^{t+1}\right)}{D^{t}(x^{t},y^{t})}$ from 2002 to 2011, and the cross-period terms $\frac{D^{t}\left(x^{t},y^{t}\right)}{D^{t+1}(x^{t},y^{t})}, \frac{D^{t}\left(x^{t+1},y^{t+1}\right)}{D^{t+1}(x^{t+1},y^{t+1})}$ from years 2002 to 2011. I first present the sample average Malmquist index which I generate using a geometric average to gain perspectives on the drivers of productivity in the sample. I also take the geometric average of the sample's TEC and FS terms. Figure (5) shows a time series of the Malmquist Index and its components.

Figure 5: Sample Average Malmquist Index, Frontier Shift, and Technical Efficiency Change

The sample tended to experience progressive TEC movements over two or three years before regressing for another two to three years. The average TEC and the average FS are negatively correlated over time. There could be several of reasons for this. The first is that technological change could be occurring where a small number of farms incorporate more productive practices while the rest of the sample catches up in the following years. Because the frontier is regressing every couple of years, it is more likely that this pattern is due to heterogeneous weather shocks affecting the productivity measures. Looking at the TEC and FS terms separately shows the relative importance of the FS term in the Malmquist Index. Figure (6) shows the TEC and FS values by the year together. Like figure (5), this also shows that TEC is generally negatively dependent about one. The figure reveals a strong negative linear relationship between the two components of the Malmquist Index. When the sample experiences technically improving frontier shifts, many of the individual farmers are further away from the frontier. When the sample experiences a technically regressing frontier shift, many farmers are closer to the new frontier. This negative linear relationships suggests that many farmers in the sample are not actually changing their input-output decisions and could be an indication heterogeneous weather shocks impacting distinct farmers in the sample at different periods in time. Figure (6) also highlights that the FS term was below or close to one in all but one year that the Malmquist Index was below one (2003, 2008, 2010, and 2011). This suggests that the FS term is relatively more important.

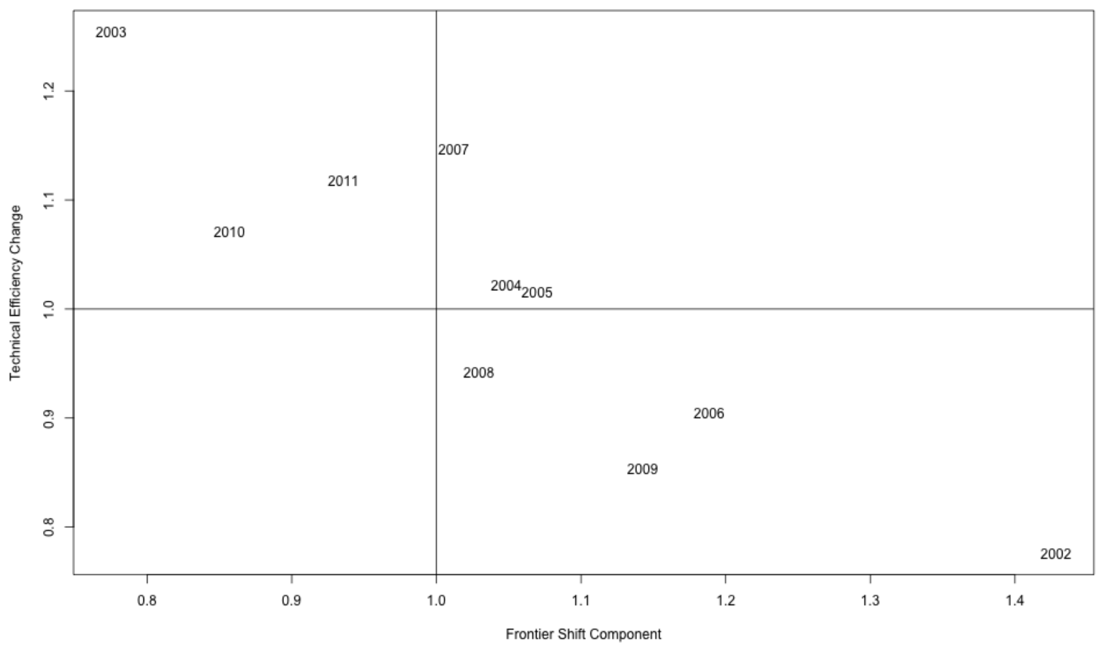


Figure 6: Average Frontier Shift and Technical Efficiency Change Terms By Year (t+1)

With the relative importance of the frontier shift term in mind, I now examine the components of the frontier shifts. Recall that there are four types of strategy shifts. A positive-positive (PP) strategy shift occurs when $\frac{D^t(x^t,y^t)}{D^{t+1}(x^t,y^t)} > 1$ and $\frac{D^t(x^{t+1},y^{t+1})}{D^{t+1}(x^{t+1},y^{t+1})} > 1$ a negative-negative (NN) shift occurs when $\frac{D^t(x^t,y^t)}{D^{t+1}(x^t,y^t)} < 1$ and $\frac{D^t(x^{t+1},y^{t+1})}{D^{t+1}(x^{t+1},y^{t+1})} < 1$, a positive-negative (PN) shift occurs when $\frac{D^t(x^t,y^t)}{D^{t+1}(x^t,y^t)} > 1$ and $\frac{D^t(x^{t+1},y^{t+1})}{D^{t+1}(x^{t+1},y^{t+1})} < 1$, and a negative-positive (NP) shift occurs when $\frac{D^t(x^t,y^t)}{D^{t+1}(x^t,y^t)} < 1$ and $\frac{D^t(x^{t+1},y^{t+1})}{D^{t+1}(x^{t+1},y^{t+1})} > 1$. Table (2) shows the strategy shifts by year. Plotting the shifts by year in figure (7) shows that the PP strategy shifts and the NN shifts are both cyclical and negatively correlated. Since the PN and NP shifts signify definitive changes in a farm's production plan and they occurred less frequently, I compare these two shift types separately. NP and PN shifts are positively correlated with one another and with NN shifts. This suggests that when technology is degrading in the sample, groups of farmers make technically progressive movements and more farmers favorably adjust than do not.

Year	2002-2003	2003-2004	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012
PP	440	32	276	274	410	167	220	390	12	92
NP	6	13	62	32	17	70	79	13	19	33
PN	2	17	27	48	14	49	33	18	7	37
NN	2	388	85	96	9	164	118	29	412	288

Table 2: Strategy Shifts of Farmers by Year

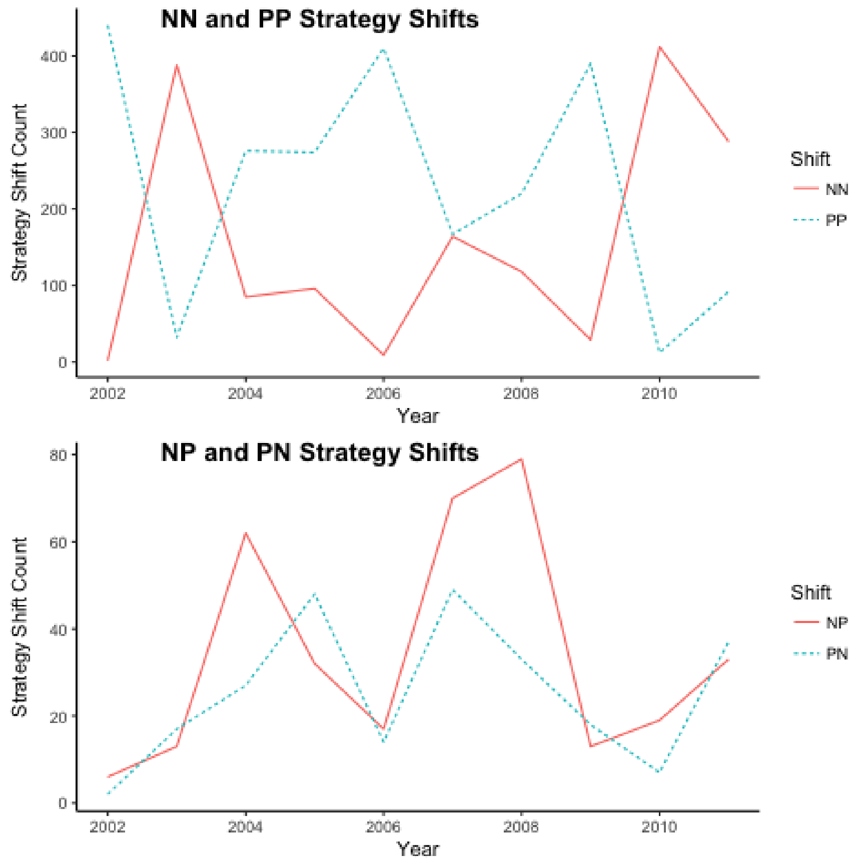


Figure 7: Strategy Shifts By Year (t+1) : Solid Lines (NP and PP)

I next examine the propensity for repeat shifts. Do I observe farmers making consistent shifts over time? Table (4) presents probability that of a farmer would exhibit one shift from period t to another shift in $t+1$. These conditional probabilities are estimated using the *markovchain* package in R. It should come as little surprise that, due to the cyclical nature of the shifts, a farmer that made a PP shift between t and $t+1$, would be likely to revert back to a NN shift and vice-versa. Around 80% or more of the experienced PP and NN shifts in each year and these terms were negatively correlated. What is interesting however, is that farms with a PP shift were more likely to make progressive changes. This could be a consequence of shocks to the production function in year $t+1$ that more savvy farmers are able to cope with. The last two columns show that given a farmers making NP or PN shifts both more likely to make an NN shift in the next period. This follows our initial expectations, that farmers making NP shifts would be more likely to exhibit PP shifts in the future. However, this could be an indication that adjusting input usage may be risky for farmers. It should be highlighted however, that farmers making a NP shift are more likely to make progressive shifts (PP,NP) in the future than farmers than regressive (PN,NN) shifts.

	Given.PP	Given.NP	Given.PN	Given.NN
PP	38.00%	60.77%	60.47%	54.49%
NP	7.97%	10.29%	8.84%	8.44%
PN	6.39%	5.14%	6.98%	5.91%
NN	47.64%	23.79%	23.72%	31.16%

Table 3: Strategy Shift Transition Matrix

While table (4) says that farmers generally do not make consistent shifts over time, it offers little other context to these shifts. I therefore run a multinomial logit that controls for temporal variation using year dummy variables with the shift terms being different "choices" the farmer could make. I include relevant weather variables to test whether the NN and PP shifts are indeed due to weather shocks. I also include farm location variables for North (as defined by the KFMA dataset) to account for differences in cropland quality.

	Strategy Shift:		
	NP	PN	PP
	(1)	(2)	(3)
Intercept	−0.306*	−0.041	−0.447
	(0.085)	(0.412)	(0.27)
Age	−0.0019 **	0.0004	0.001
	(0.016)	(0.305)	(0.356)
DR2	0.002	0.0309*	−0.0421
	(0.475)	(0.093)	(0.417)
Crop_over_Op	−0.0048	0.0005	0.0013
	(0.401)	(0.49)	(0.496)
dday10C	0.0001*	−0.0001	0.0001
	(0.07)	(0.241)	(0.418)
soil_moisture	−0.0003*	−0.0002	−0.0002
	(0.08)	(0.16)	(0.438)
North	0.0321 **	−0.0174	−0.0214
	(0.047)	(0.143)	(0.364)
Acreage_Index	0.0351	0.126 **	0.78 ***
	(0.374)	(0.029)	(0.004)
Herfindahl_Index	−0.0285	0.0201	−0.908 ***
	(0.316)	(0.312)	(0.004)
Observations	4,500		
Log Likelihood	-3,380.92		
Akaike Inf. Crit.	6,869.857		
Note:			*p<0.1; **p<0.05; ***p<0.01 p-values in ()

Table 4: Year-Dummy Multinomial Logit Model Results

Table (4) shows the marginal effects from a multinomial logit model accounting for temporal effects using yearly dummy variables. The four "choices" in the multinomial logit are the shift types with the negative-negative (NN) shift type being the reference choice. The results show that that younger farmers are significantly more likely to be an NP shifter. Additionally, weather variables signficantly impact the propensity to choose more efficient input bundles. The county's annual 10°C seasonal degree growing days, postively impacts the farm's propensity to be an NP shifter. The county's soil moisture negatively correlated with the farmer's propensity to be an NP shifter. Soil characteristics is also a relevant factor as the North, variable, the instrument for soil quality was also positively correlated with the farmer's propensity of choosing to NP shift.

One of the fundamental features of strategy shifts analysis is the focus on proportional input choices and not proximatey to the frontier itself. This means that in the NP and PN shift-types I can actually attribute variables to the *changes* in input vectors while the PP and NN are more an indication of the general location of input vectors. Shift types could be basing their calculations off identical input decisions from year-to-year. It is therefore expected that variables such as weather would not impact the farmer's likelihood of being a PP shifter. The marginal effects table shows that this is the case as the total acreage size index has a positive and significant effect on probability of a farmer being a PP shifter. Additionally, farmers with a less concentrated crop profile also are more likely to be a PP shifter. This indicates that farms that are larger and have a higher degree of crop diversity are more resiliant to changing conditions. The lack of statistically significant weather effects is important considering the high degree of correlation between the FS and TEC terms (figure 6). Because the Malmquist Index is a function of the TEC term it is likely that weather will be a more significant component in Malmquist model. If this is the case then it would give a reason for caution when using and interpreting the Malmquist Index to measure efficiency changes over time. In later versions of the paper, I will run a linear model using the biennial Malmquist Index as the dependent variable. This specification will allow for examining a joint frontier between pairs of periods and will relax the assumption of constant returns to scale technologies (Pastor, Asmild, and Lovell, 2011).

5 Conclusions

Examining each of the individual components inside the frontier shift term provides important information on technological progress that is taking place in a sample of DMUs. While the frontier shift is only one component of measuring productivity change, it is an important one. If a farmer were closer to the frontier in period $t+1$ versus t, ($TEC > 1$), but the farm exhibited a NN or PN shift, I can tell that the farm did not escape the isoquant in period t, a potential consequence of new technology. On the other hand if $TEC < 1$ but the farmer exhibited a PP or NP shift, it is possible that the farm escaped the isoquant in period t. What this means is that the frontier shift provides necessary conditions for technological improvement while the TEC does not.

These terms offer more context to the frontier shift that is obscured through averaging in the Malmquist index. This added context is important in this analysis since the frontier shift term was relatively more important and on average around 15% of the sample made a NP or PN strategy change. Noticing using these strategy shifts, I can determine whether a farm changed its production plan and assess whether these changes have the potential to exploit technical progress. Since these terms are needed in order to disaggregate the Malmquist Index into its FS and TEC components, strategy shift analysis is relatively easy to carry out in general nonparametric analyses on productivity changes. Anlaysis of strategy shifts can be useful in extension applications. Using secondary analysis on strategy shifts could provide insights on constraints that keep farmers from operating on progressing sections of the isoquant.

Relatively large farms and farms that are more diverse were more likely to experience PP shifts from year to year. Larger farms with higher debt to asset ratios also more likely to technically regress. This suggests that leveraging issues carry over from one year to the next and hinder technical improvement. Weather has a significant effect on technical improvement over time. Farms with more 10° growing days tended to be ones that relatively improved. This suggests that farmers make technical progress after favorable weather conditions.

On a more technical note,the robustness of DEA models is a subject of current research. The output of DEA models rely on benchmarked efficiency between farmers within a sample. Since this output enters second stage regressions, the model may suffer from measurement error if the sample is not representative and can be sensitive to changes in farmers included in the sample. If these models are especially sensitive to sampling changes, it may lead to biased models or high variance in efficiency estimates. Research is currently being done by randomly dropping or sampling the full groups of decision makers. I conjecture that a strategy shift approach is more robust than using a standard Malmquist Index. I believe this is the case because the strategy shifts are represented as binary variables and not a continous variable and will therefore is not as likely to change from sampling. Additionally, since the strategy shift approach makes use of only the frontier shift component, it should be less volatile than the Malmquist approach. In further revisions, I will use a bootstrapping approach similar to Simar and Wilson (1999) to compare the robustness of the strategy shift approach and the Malmquist approach (Simar and Wilson, 1999). In addition, further revisions will also include analysis of input bias in the sample to identify inputs that contribute to the frontier shift component changes over time.

References

2016. “PRISM Climate Group.” http://prism.oregonstate.edu.

Caves, D.W., L.R. Christensen, and W.E. Diewert. 1982. “The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity.” *Econometrica* 50:1393.

Charnes, A., W.W. Cooper, and E. Rhodes. 1978. “Measuring the Efficiency of Decision Making Units.” *European Journal of Operational Research* 2:429–444.

Chen, Y., and A.I. Ali. 2004. “DEA Malmquist Productivity Measure: New Insights with an Application to Computer Industry.” *European Journal of Operational Research* 159:239–249.

Coble, K.H., T.O. Knight, R.D. Pope, and J.R. Williams. 1996. “Modeling Farm-Level Crop Insurance Demand With Panel Data.” *American Journal of Agricultural Economics* 78:439–447.

Coelli, T.J., and G.E. Battese. 1996. “Identification of Factors Which Influence the Technical Inefficiency of Indian Farmers.” *Australian Journal of Agricultural Economics* 40:103–128.

Färe, R., S. Grosskopf, B. Lindgren, and P. Roos. 1992. “Productivity Changes in Swedish Pharamacies

1980–1989: A Non-Parametric Malmquist Approach." In *International Applications of Productivity and Efficiency Analysis*. Springer, pp. 81–97.

Giannakas, K., R. Schoney, and V. Tzouvelekas. 2001. "Technical Efficiency, Technological Change and Output Growth of Wheat Farms in Saskatchewan." *Canadian Journal of Agricultural Economics/Revue Canadienne D'Agroeconomie* 49:135–152.

Gonzalo, J.A., and M. Alfonseca. 2016. "WORLD POPULATION GROWTH." *World Population: Past, Present, & Future*, pp. 29.

Langemeier, M.R. 2003. "Kansas Farm Management SAS Data Bank Documentation." Unpublished, Dept. of Agricultural Economics Kansas State University.

Mishra, A.K., R.P. Williams, J.D. Detre, et al. 2009. "Internet Access and Internet Purchasing Patterns of Farm Households." *Agricultural & Resource Economics Review* 38:240.

Pastor, J.T., M. Asmild, and C.K. Lovell. 2011. "The Biennial Malmquist Productivity Change Index." *Socio-Economic Planning Sciences* 45:10–15.

Simar, L., and P.W. Wilson. 1999. "Estimating and bootstrapping Malmquist indices." *European Journal of Operational Research* 115:459–471.

Sotnikov, S. 1998. "Evaluating the Effects of Price and Trade Liberalisation on the Technical Efficiency of Agricultural Production in a Transition Economy: The Case of Russia." *European Review of Agricultural Economics* 25:412–431.

Sutch, R. 2011. "The Impact of the 1936 Corn Belt Drought on American Farmers' Adoption of Hybrid Corn." In *The Economics of Climate Change: Adaptations Past and Present*. University of Chicago Press, pp. 195–223.

Wang, S.L., P. Heisey, D. Schimmelpfennig, and V.E. Ball. 2015. "Agricultural Productivity Growth in the United States: Measurement, Trends, and Drivers." *Economic Research Service, Paper No. Err-189*, pp. .