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The Contributions of Weather, Technological Change, and Adaptation to Agricultural Productivity Growth

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1 Introduction

Much of what is known about the production effects of climate change comes from agricultural studies (Dell, Jones, and Olken 2014). Broadly speaking, two approaches have evolved for investigating the effects of weather on agricultural production. One, often referred to as the "production-function" or "agronomic" approach, uses experimental data to construct a "production function" that incorporates climatic factors. These production functions are then combined with data from climate-change models to approximate possible climatic effects upon production levels (see for example, Adams 1989; Adams et al. 1990; Rosenzweig and Parry 1994). Another, often referred to as Ricardian, relates economic returns from farming to weather variates econometrically and then links those results to climate-change models (see for example, Mendelsohn, Nordhaus, and Shaw 1994; Schlenker, Hanemann, and Fisher 2005; Deschênes and Greenstone 2007; Fisher, Hanemann, Roberts, and Schlenker 2012; Yang and Shumway 2016).

This paper examines the interrelationship between weather variates and agricultural production from a different perspective. It examines the interplay between aggregate agricultural productivity measures and weather variates. US agriculture offers a peculiarly appropriate laboratory for such an analysis because it has proven capable of continuously increasing aggregate production with minimal increases in aggregate input use. This tendency, first noted almost seven decades ago by Barton and Cooper (1948), has now persisted for a century (Barton and Cooper 1948; Ball, Wang, Nehring, and Mosheim 2015) and distinguishes agriculture from many other industrial sectors where the primary driver of production growth is input growth (Jorgenson, Ho, and Stiroh 2005).[1]

Working from Abramovitz's (1956) hypothesis that the measured difference between output growth and input growth, the so-called Solow residual, was a "measure of our ignorance", early agricultural productivity studies strove to eliminate this residual. These early efforts culminated in Griliches (1963). His classic analysis emphasized the importance of changes in input quality and economies of scale rather than technical change in explaining observed productivity growth. Since that time, however, US agriculture has undergone a massive consolidation. Moreover, the quality corrections advocated by Griliches' (1960; 1963) were long ago incorporated into total factor productivity (TFP) calculations. But the residual remains, and the conventional wisdom is that most of aggregate US agricultural output growth results from technical progress (Jorgenson, Ho, Stiroh 2005; Wang, Heisey, Schimmelfpfennig, and Ball 2015).

Although US agricultural productivity has grown steadily, that growth has become quite variable. Figure 1, which depicts annual growth rates of US agricultural TFP from 1948-2013, illustrates. Prior to 1970, growth was relatively stable. But around 1970, it became less stable. Some of this instability is attributable to external factors including the first and second oil shocks and gov-

[1] While aggregate agricultural input use has remained remarkably stable for almost a century, the composition of that aggregate input has changed markedly over the last 40 years as the usage of intermediate inputs has steadily supplanted both capital (including land) and labor in the aggregate input. Ball, Wang, Nehring, and Mosheim (2015) contains a detailed discussion of this changing composition.

ernment production-reduction programs. But even after adjusting for these factors, US agricultural TFP growth after 1990 was clearly more variable than it had been prior to 1970.

Another perspective on the same phenomenon comes from examining US state-level agricultural TFP patterns. In Figure 2, we have plotted smoothed estimated kernel densities for state-level agricultural TFP for each of the 48 contiguous US states over two 14-year time periods 1961-1974 and 1991-2004. As demonstrated by the apparent mean shift, average state-level TFP grew dramatically between these two periods. Given the observed level of national agricultural productivity growth, this mean shift is to be expected. But the 1991-2004 TFP distribution is also more platykurtic than that for 1961-1974. In the 1961-1974 period the observed kurtosis is 6.9647,[2] with a standard error of 0.1882 indicative of a leptokurtic distribution with a long, fat tail. For 1991-2004, the calculated kurtosis is 3.5515 indicative of a slightly leptokurtic and more symmetric distribution.

A natural suspect for this increased variability is weather. There seems little doubt that US weather patterns changed during the last half of the 20th century. And some empirical evidence suggests that regional weather patterns play a significant role in explaining national-level agricultural TFP variability (Liang, Wu, Chambers et al. 2017). But even though weather-determined factors, such as precipitation, are inputs to agricultural production, they are typically excluded in agricultural TFP calculations. Thus, while official statistics account for inputs, such as climate-control and irrigation, that are devoted to mitigating the effects of adverse weather outcomes, the weather events driving these expenditures are absent from the accounting.

This paper investigates the interaction between US state-level agricultural TFP growth and weather outcomes using growth-accounting techniques. The focus is on determining whether that interaction was different at the end of the 20th century than in the 1960s. To that end, United States Department of Agriculture (USDA) state-level productivity data for 1960-2004 are combined with matching data on growing degree days and moisture (Schlenker and Roberts 2008, 2009). The combined data are used to construct an aggregate agricultural production frontier that incorporates observed weather variates into the empirical approximation of the technology. The constructed frontier is used to decompose observed state-level agricultural TFP growth into four components: technical change, weather-related shifts in the frontier, aggregate input growth, and adaptation to the frontier.

The productivity frontier is developed using mathematical programming techniques. These techniques do not require specific assumptions on economic behavior or functional form. The analysis focuses on comparing agricultural TFP performance during two 14-year sub-periods 1961-74 and 1991-2004 that correspond to the beginning and the end of our sample period. The periods are chosen to omit the policy-driven shocks to agricultural TFP of the Payment-In-Kind (PIK)

[2] Kurtosis is calculated as,

$$\frac{(n-1)}{(n-2)(n-3)}\left((n+1)\frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2\right)^2}-3(n-1)\right)+3$$

(Harald Cramér 1946, pp. 386-387).

agricultural programs of the early 1980s. The empirical analysis suggests that the perceived changes in state-level TFP growth as captured by its average and its distribution can largely be attributed to technical change and changes in the pattern of states adopting existing technical improvements. And while weather-related effects are important for some key states, weather effects on the average state-level TFP growth and on the distribution of TFP growth appear minimal.

In what follows, the basic model is developed. The process by which state-level data is used to construct an approximation to the agricultural production frontier is detailed. The traditional TFP measure is decomposed, using index method techniques, into four parts relative to that frontier. The four parts are a weather index, an index of technical change, an efficiency or adaptation measure, and a measure of true TFP or scale effects. We then briefly discuss a computational issue associated with our approach and how that issue can be used to infer information about weather-related effects. The empirical analysis then follows. Average results, results for the distributions of the various measures, and results for four subgroups of states are then discussed. The paper then concludes.

2 The Basic Model

2.1 Constructing the Productivity Frontier

Our data consist of annual observations for the period 1960-2004 for the 48 contiguous US states on total agricultural output, total agricultural input, and two measured weather variates. The first weather variate consists of state-level observations on degree days (DD) between 8^o and 30^o Celsius between March and August, and the second consists of inches of precipitation over the same period.[3]

The essential idea is to use these data to construct an empirical approximation to the aggregate production technology relating aggregate output to the aggregate input measures and weather variates. By incorporating weather variates as inputs to the production process, we recognize the fundamentally stochastic nature of agricultural production that derives from its dependence upon physical inputs that are beyond the producer's control. This contrasts strongly with many existing studies of agricultural TFP that are built upon a model of a nonstochastic technology that denies the essential nature of agricultural production.[4]

To approximate the technology underlying these data, we rely on techniques originally developed

[3] All of our data were obtained from V. Eldon Ball of the Economic Research Service, United States Department of Agriculture to whom we are deeply indebted.

[4] A sizable literature has evolved on attempting to explain measured aggregate agricultural TFP. Alston, Norton, and Pardey (1995) provide a thorough introduction and explanation of the approach and the technical issues involved. The basic approach is to construct an aggregate TFP measure and then in a second stage use regression analysis to relate those measures to potential "explanatory variables" or "productivity drivers", some of which include weather variates.

by Farrell (1957) and Afriat (1972) as extended by a number of authors under the general rubrics of "nonparametric productivity analysis" and "data envelopment analysis" (Charnes, Cooper, Golany, Seiford, and Stutz 1985; Färe, Grosskopf, Lovell, and Pasurka 1989; Färe, Grosskopf, Lovell, and Yaisawarng 1993; Byrnes, Färe, Grosskopf, and Lovell, 1988; Kumar and Russell 2002; Henderson and Russell 2005).[5] The basic idea behind this approach, which has its ultimate roots in the activity-analysis model of Koopmans (1951), is that each observed input-output combination (process) can be recognized as one manifestation of the feasible technology. That underlying technology is then approximated by incorporating these observed processes with basic axioms of production to arrive at a conservative approximation to the underlying technology. The ultimate result is an approximation that can be expressed completely in terms of inequalities involving linear combinations of the observed processes. That polyhedral approximation to the technology can be analyzed using relatively simple mathematical programming techniques.

The first step is to envelop the observed data on output, inputs, and weather variates by taking their convex hull (the smallest convex set containing all the observed data points). This envelopment gives the smallest set of outputs, inputs, and weather variates that are consistent with the observed data *and* the existence of convex production technology. This convex hull thus represents the most conservative approximation to the data consistent with a convex technology. After that envelopment is accomplished, additional assumptions on the underlying technology are invoked to extend that approximation.

Denote aggregate agricultural output for the k^{th} state at time t by y_{tk}, aggregate agricultural input use for the k^{th} state at time t by x_{tk}, and the two-vector of measured weather variates for the k^{th} state at time t by w_{tk}. The convex hull of these observations is given by

$$C(t) = \left\{ \begin{array}{c} (y,x,w) : y = \sum_{j=1}^{t}\sum_{k=1}^{48} \mu_{jk} y_{jk},\ w = \sum_{j=1}^{t}\sum_{k=1}^{48} \mu_{jk} w_{jk},\ x = \sum_{j=1}^{t}\sum_{k=1}^{48} \mu_{jk} x_{jk}, \\ 1 = \sum_{j=1}^{t}\sum_{k=1}^{48} \mu_{jk},\ \mu_{jk} \geq 0, j = 1, \ldots, t \end{array} \right\}.$$

The next step in forming the approximation is to assume that if a particular (y, x, w) is technically feasible any radial contraction of that (y, x, w) is also technically feasible. Intuitively, this ensures that the approximation to the technology does not exhibit increasing returns and that inaction is technically feasible.[6] Mathematically, this is accomplished by replacing the μ_{jk} "activity variates" in $C(t)$ with new activity variates, call them λ_{jk}, while requiring the latter's sum to be less than or equal to one as opposed to one for the former. The result is

$$N(t) = \left\{ \begin{array}{c} (y,x,w) : y = \sum_{j=1}^{t}\sum_{k=1}^{48} \lambda_{jk} y_{jk},\ w = \sum_{j=1}^{t}\sum_{k=1}^{48} \lambda_{jk} w_{jk},\ x = \sum_{j=1}^{t}\sum_{k=1}^{48} \lambda_{jk} x_{jk}, \\ 1 \geq \sum_{j=1}^{t}\sum_{k=1}^{48} \lambda_{jk},\ \lambda_{jk} \geq 0, j = 1, \ldots, t \end{array} \right\}$$

[5] Färe, Grosskopf, and Lovell (1994) contains a relatively complete survey in textbook form of the early economic work on nonparametric productivity analysis. After the contribution of Charnes, Cooper, and Rhodes (1978), a closely related literature has developed in parallel in the area of operations research. These contributions have been summarized in Charnes, Cooper, Lewin and Seiford (1994).

[6] See the discussion in the Infeasibilities section for more on this assumption.

The final step is to impose "free disposability" of (y,x) upon the observations. This is accomplished by converting the equalities in $N(t)$ relating to (y,x) into weak inequalities. In intuitive terms, this ensures that the marginal product of x in producing y is nonnegative. The resulting approximation to the technology at time t is

$$T(t) = \left\{ \begin{array}{c} (y,x,w) : y \leq \sum_{j=1}^{t}\sum_{k=1}^{48}\lambda_{jk}y_{jk},\ w = \sum_{j=1}^{t}\sum_{k=1}^{48}\lambda_{jk}w_{jk},\ x \geq \sum_{j=1}^{t}\sum_{k=1}^{48}\lambda_{jk}x_{jk}, \\ 1 \geq \sum_{j=1}^{t}\sum_{k=1}^{48}\lambda_{jk},\ \lambda_{jk} \geq 0, j = 1,\ldots,t \end{array} \right\}$$

There are several things to note. First, free disposability is not imposed upon the weather variates in our approximation to the technology. This reflects the fact that either too much heat or too much moisture applied to a fixed x can be destructive to the agricultural production process. In fact, one of the main biological problems associated with plant growth is heat stress while another is excess moisture. Thus, where our approximation requires $x \geq \sum_{j=1}^{t}\sum_{k=1}^{48}\lambda_{jk}x_{jk}$, for the weather variates it requires $w = \sum_{j=1}^{t}\sum_{k=1}^{48}\lambda_{jk}w_{jk}$.

Second, technical change is assumed to be progressive, that is, for $t' > t$, $T(t) \subseteq T(t')$. This can be ascertained by noting, for example, that $T(1)$ is constructed from the state-level observations for the 48 contiguous states for the first-year in the sample. $T(2)$ is based on the observations used in $T(1)$ plus the observations from the second year and so on. Our rationale for imposing progressive technical change is simple. It seems impossible to believe that technical know how for a given set of inputs (including weather, climate conditions, etc.) would degrade in modern times. As Kumar and Russell (2002) memorably queried: "Does knowledge decay? Were "blueprints" lost?"

Because confusion appears to exist in some quarters on this issue, it is important to emphasize that this claim presumes proper accounting of all factors affecting production. It is clear, for example, that certain practices can degrade the natural-resource base to preclude achieving previous levels of yields from application of a given bundle of variable inputs (including weather and other climate-controlled factors). Soil exhaustion by improper rotational techniques is an obvious example from agriculture. In some quarters, this has been perceived as technical regression. That is incorrect. Properly speaking, such examples do not constitute a change in what is technically possible from a given bundle of inputs, but either a degraded quasi-fixed factor of production or a degraded flow from such a factor. Modern accounting practices for quasi-fixed inputs, such as land and capital, make explicit corrections using hedonic and other methods in an attempt to ensure measured resource flow units are consistently defined from one period to the next (Ball, Wang, and Nehring 2015).

From this representation of the underlying technology, we can construct the following representation of *the maximal feasible output* at time t as conditioned by aggregate input and the weather variates as

$$f_t(x,w) = \max \left\{ \begin{array}{c} \sum_{j=1}^{t}\sum_{k=1}^{48}\lambda_{jk}y_{jk} : w = \sum_{j=1}^{t}\sum_{k=1}^{48}\lambda_{jk}w_{jk},\ x \geq \sum_{j=1}^{t}\sum_{k=1}^{48}\lambda_{jk}x_{jk}, \\ 1 \geq \sum_{j=1}^{t}\sum_{k=1}^{48}\lambda_{jk},\ \lambda_{jk} \geq 0, j = 1,\ldots,t \end{array} \right\}.$$

2.2 The Components of TFP Change

Because the empirical procedure relies on enveloping observed data, some observations will fall below the piece-wise linear approximation to the productivity frontier. The observations that lie inside the productivity frontier are usually construed as being technically *inefficient*. A measure of that inefficiency is given by the ratio

$$E_t\left(y_t, x_t, w_t\right) = \frac{y_t}{f_t\left(x_t, w_t\right)}$$

that relates observed output, y_t, to the maximal feasible output for $\left(x_t, w_t\right)$, $f_t\left(x_t, w_t\right)$. If $E_t\left(y_t, x_t, w_t\right) = 1$, it reflects "state-of-the-art" performance relative to that frontier signalling that the state in question has completely adapted to existing technical possibilities. If $E_t\left(y_t, x_t, w_t\right) < 1$, its adaptation to the best-practice frontier remains imperfect.

Using $E_t\left(y_t, x_t, w_t\right)$ and decomposition techniques pioneered by Färe, Grosskopf, Norris, and Zhang (1994), Kumar and Russell (2002), and Henderson and Russell (2005) observed changes in a TFP index over time can be decomposed into four components. At time t, the index of TFP relative to the base period 0 is defined by[7]

$$TFP\left(t, 0\right) \equiv \frac{y_t / x_t}{y_0 / x_0}.$$

Using $E_t\left(y_t, x_t, w_t\right)$, that index can be rewritten as

$$\begin{aligned}
\frac{y_t/x_t}{y_0/x_0} &= \frac{E_t\left(y_t, x_t, w_t\right) f_t\left(x_t, w_t\right) x_0}{E_0\left(y_0, x_0, w_0\right) f_0\left(x_0, w_0\right) x_t} \\
&= \left(\frac{f_0\left(x_t, w_t\right) f_t\left(x_t, w_t\right)}{f_0\left(x_t, w_0\right) f_t\left(x_t, w_0\right)}\right)^{\frac{1}{2}} \left(\frac{f_t\left(x_0, w_0\right) f_t\left(x_t, w_t\right)}{f_0\left(x_0, w_0\right) f_0\left(x_t, w_t\right)}\right)^{\frac{1}{2}} \left(\frac{f_0\left(x_t, w_0\right)/x_t}{f_0\left(x_0, w_0\right)/x_0} \frac{f_t\left(x_t, w_0\right)/x_t}{f_t\left(x_0, w_0\right)/x_0}\right)^{\frac{1}{2}} \frac{E_t\left(y_t, x_t, w_t\right)}{E_0\left(y_0, x_0, w_0\right)}.
\end{aligned}$$

The second equality breaks the observed index into four separate measures.[8]

[7] Given the presence of w in f, the "TFP" measure that we employ is more appropriately interpreted as a partial-productivity measure giving the "productivity of x". A true total factor productivity measure would directly incorporate the weather variates into the calculation of the aggregate input. However, y/x is the standard or conventional TFP measure as calculated by USDA, and so we adhere to that naming convention in our discussion.

[8] Geometric averages are used in the decomposition because, for example, both

$$\frac{y_t/x_t}{y_0/x_0} = \frac{E_t\left(y_t, x_t, w_t\right) f_t\left(x_t, w_t\right) f_0\left(x_t, w_t\right) f_0\left(x_t, w_0\right) x_0}{E_0\left(y_0, x_0, w_0\right) f_0\left(x_t, w_t\right) f_0\left(x_t, w_0\right) f_0\left(x_0, w_0\right) x_t},$$

and

$$\frac{y_t/x_t}{y_0/x_0} = \frac{E_t\left(y_t, x_t, w_t\right) f_t\left(x_0, w_0\right) f_t\left(x_t, w_t\right) f_t\left(x_t, w_0\right) x_0}{E_0\left(y_0, x_0, w_0\right) f_0\left(x_0, w_0\right) f_t\left(x_t, w_0\right) f_t\left(x_0, w_0\right) x_t},$$

decompose observed productivity growth into a technical change index, a weather index, and an efficiency component. In the former, the weather index is $\frac{f_t\left(x_t, w_t\right)}{f_t\left(x_t, w_0\right)}$ while in the latter it is $\frac{f_0\left(x_t, w_t\right)}{f_0\left(x_t, w_0\right)}$. One describes the weather effect relative to the t-relevant technology and the other to the 0-relevant technology. The same is true for the index of the aggregate input effect. Similarly for the technical change index, one makes the comparison for the t-relevant data and the other for 0-relevant data. In each case, either a different data point or a different f is used as the base of comparison, and will typically result in different measures much in the same manner that more traditional Laspeyres and Paasche indices differ from one another. And unless the underlying technology satisfies a restrictive neutrality condition, the

The first measure,

$$\left(\frac{f_0\left(x_t,w_t\right)f_t\left(x_t,w_t\right)}{f_0\left(x_t,w_0\right)f_t\left(x_t,w_0\right)}\right)^{\frac{1}{2}},$$

is the geometric average of two measures of how changes in w affect maximal production at time t and at time 0 holding aggregate input utilization fixed at x_t.[9] We refer to it as the *weather component of the productivity index.*

The second component,

$$\left(\frac{f_t\left(x_0,w_0\right)f_t\left(x_t,w_t\right)}{f_0\left(x_0,w_0\right)f_0\left(x_t,w_t\right)}\right)^{\frac{1}{2}},$$

represents the geometric average of the shift in the production function between 0 and t as evaluated at the observed aggregate input and weather variates for 0 and t. We refer to it as the *technical change component of the productivity index.*

The third component, the *input component of the productivity index,*

$$\left(\frac{f_0\left(x_t,w_0\right)/x_t}{f_0\left(x_0,w_0\right)/x_0}\frac{f_t\left(x_t,w_0\right)/x_t}{f_t\left(x_0,w_0\right)/x_0}\right)^{\frac{1}{2}}$$

is the geometric average of the index of total factor productivity for input x_t relative to x_0 computed using maximal feasible output for the 0 period technology (holding weather fixed at w_0),

$$\frac{f_0\left(x_t,w_0\right)/x_t}{f_0\left(x_0,w_0\right)/x_0},$$

and the same TFP index computed for the t period technology,

$$\frac{f_t\left(x_t,w_0\right)/x_t}{f_t\left(x_0,w_0\right)/x_0}$$

Each component differs from $TFP\left(t,0\right)$ by replacing observed output with maximal feasible output (holding w_0 fixed). Thus, each component may be thought of as the *potential* TFP of x_t relative to x_0 for the respective technologies. A standard computation, however, also shows that if average product, $f_k\left(x,w\right)/x$ for $k=0,t$, is increasing in x, some economies of scale in x exist as one moves along the maximal output frontier *holding* w *constant.* Thus, if, say, $\frac{f_t(x_t,w_0)/x_t}{f_t(x_0,w_0)/x_0}>1$, it provides evidence of exploitation of existing scale economies in x for technology t.

resulting decompositions will differ. Caves, Christensen, and Diewert (1982), Färe, Grosskopf, Norris, and Zhang (1994), and Kumar and Russell (2002) suggest resolving the resulting indeterminacy by using the "Fisher ideal" version of the two measures. Adopting that suggestion results in the geometric averaging procedure.

[9] Another possibility is to hold the input bundle constant at x_0,

$$\left(\frac{f_0\left(x_0,w_t\right)f_t\left(x_0,w_t\right)}{f_0\left(x_0,w_0\right)f_t\left(x_0,w_0\right)}\right)^{\frac{1}{2}},$$

in computing the weather index. This measure can be geometrically averaged with the current measure to generate an even more general weather index. But as a practical matter, this construction exacerbates the infeasibility problem discussed below and so was avoided.

The final component of the decomposition,

$$\frac{E_t\left(y_t, x_t, w_t\right)}{E_0\left(y_0, x_0, w_0\right)}$$

compares the relative efficiency with which the technology is used in time t and in time 0. If it is greater than one, the state has moved closer to the frontier between time 0 and time t signalling adaptation to changing technical practice. If it is less than one, the state has moved further away from the frontier, signalling failure to keep up with the "best-practice" technology.

Logarithmic differences in agricultural TFP, which approximate percentage changes, between t and 0 can thus be decomposed into four parts:

$$\begin{aligned}\ln\frac{y_t}{x_t}-\ln\frac{y_0}{x_0} &= T\Delta_{t,0}\left(w_t, w_0, x_t, x_0\right)+W\Delta_{t,0}\left(w_t, w_0, x_t, x_0\right)+X\Delta_{t,0}\left(w_t, w_0, x_t, x_0\right)\\ &\quad +E\Delta_{t,0}\left(y_t, y_0, w_t, w_0, x_t, x_0\right),\end{aligned}$$

where the *technical change indicator* is

$$T\Delta_{t,0}\left(w_t, w_0, x_t, x_0\right)=\frac{1}{2}\left[\ln f_t\left(x_t, w_t\right)-\ln f_0\left(x_t, w_t\right)+\ln f_t\left(x_0, w_0\right)-\ln f_0\left(x_0, w_0\right)\right],$$

the *weather change indicator* is

$$W\Delta_{t,0}\left(w_t, w_0, x_t, x_0\right)=\frac{1}{2}\left[\ln f_t\left(x_t, w_t\right)-\ln f_t\left(x_t, w_0\right)+\ln f_0\left(x_t, w_t\right)-\ln f_0\left(x_t, w_0\right)\right],$$

the *input change indicator* is,

$$X\Delta_{t,0}\left(w_t, w_0, x_t, x_0\right)=\frac{1}{2}\left[\ln\left(f_t\left(x_t, w_0\right)x_0\right)-\ln\left(f_t\left(x_0, w_0\right)x_t\right)+\ln\left(f_0\left(x_t, w_0\right)x_0\right)-\ln\left(f_0\left(x_0, w_0\right)x_t\right)\right]$$

and the *efficiency change indicator* is

$$E\Delta_{t,0}\left(y_t, y_0, w_t, w_0, x_t, x_0\right)=\ln E_t\left(y_t, x_t, w_t\right)-\ln E_0\left(y_0, x_0, w_0\right).$$

2.3 Infeasibilities

Because we do not require the weather inputs to be freely disposable and because our empirical technique uses conservative methods to approximate the technology as applied to a panel of data, the possibility arises that some components of our decomposition of TFP change (TFPΔ) may not be calculable for certain time periods. The basic problem can be illustrated by considering two data points for, say, a single state taken at different points in time. Figure 3 illustrates the situation. There we have treated the weather variates as though they can be combined into a single variable that is measured along the axis labelled w. The aggregate agricultural input is measured along the axis labelled x and the aggregate output is measured along the axis measured y. The two points are presented in Figure 3a as (w_0, x_0, y_0) and (w_t, x_t, y_t) and we presume that 0 is the base period that precedes period t.

Under our maintained assumptions, the approximation to the period 0 technology would be given by the shaded area in Figure 3b. Because the input pair (x_t, w_t) falls outside of that shaded area, it is not consistent with producing any output using the 0 approximation to the technology. In such instances components of the productivity decomposition, for example, $f_t(w_t, x_t) / f_0(w_t, x_t)$, are not calculable.

Such problems could be resolved by using "less conservative" approximating procedures. For example, if one imposes free disposability upon the weather variate, the 0 approximation to the technology now extends parallel to the w axis (at vertical level y_0) towards the bottom of the figure (see panel c of Figure 3). And, one can now calculate $f_0(w_t, x_t)$ using this "less conservative" approximation. But making this extension requires imposing global structure on a technology that is known to be repeatedly violated. For that reason, it is avoided in our empirical analysis.

The empirical presence of infeasibilities is more than *just a technical difficulty.* It communicates information, albeit conservatively, about the changing structure of technical possibilities. As Figure 3b illustrates, components of the decomposition are not calculable because (w_t, x_t) falls outside the range of actual experience at time 0. And thus incorporating it into the technology approximation for time 0 requires extrapolating beyond practical experience. This, of course, can be achieved by imposing appropriate statistical structure and fitting curves. But that requires making further assumptions beyond ours on the structure of the technology. In particular, it necessitates choosing a functional specification for the technology. And such choices are typically made on the basis of computational tractability rather than on physical plausibility.

3 Empirical Analysis

Our empirical analysis focuses on two sub periods 1961-1974 and 1991-2004. There are different ways to examine long-term, productivity-growth patterns. For example, one might simply choose the first observed period and the last observed period and perform productivity analysis across that 44 year period. Weather, however, is notoriously variable, and such a procedure risks misstating long-term weather effects as a result of choosing the comparison points. For that reason, our long-term productivity comparisons and decompositions were made across 14 different 30-year time horizons that were chosen to match our first and second sub-period. Before we look at those comparisons, we first examine each state's productivity performance relative to the productivity frontier in both sub periods.

3.1 Performance Relative to the Productivity Frontier and Adaptation

Table 1 presents summary information on calculated efficiency scores for each contiguous state for the sub periods 1961-1974 and 1991-2004. States with efficiency scores close to 1 are on or very near the productivity frontier. States with efficiency scores less than 1 fall inside the productivity frontier. Because the empirical methodology uses states on the productivity frontier to construct the empirical envelope of the observed data, it is reasonable to interpret the relatively efficient states as operating technical processes that determine the placement of the frontier, which describes best available technical practices. These are the states that have done the best job of adapting to the overall operating environment including weather patterns as captured by the measured weather variates. States lying below the frontier are less well adapted to changing technological possibilities. The further inside the frontier, the less well the state has adapted to the technical environment.

Six states (Arizona, California, Florida, Iowa, Rhode Island, and Texas) have average efficiency scores exceeding .9 for both of the sample periods. Arizona is a geographically large southwestern state, but in 2012 it ranked 32 (out of 50) in terms of value of agricultural production. Therefore, in production value terms it is on the small side. Its primary commodities are cattle, milk, animal forage, and lettuce. California is the largest agricultural state in production-value terms and has perhaps the most diverse agriculture in the United States with heavy concentrations in fruits and nuts, dairy products, vegetables, and livestock (cattle). Iowa ranks second in production-value terms and is heavily concentrated in corn, soybean, and livestock (hogs and cattle) production. Florida falls slightly above the national average in value terms ($8.46 billion in 2014). Its primary crops are oranges, nursery products, and vegetables. Rhode Island is the smallest of the 48 contiguous states in value terms ($75 million in 2014) and its minuscule production is concentrated in nursery products.[10] In 2012, Texas ranked third overall in value of agricultural production behind California and Iowa. It ranked first in livestock production value with livestock accounting for approximately three quarters of its total production value.

Arizona (3), California (2), Florida (1), and Iowa (4) had the four highest measured TFPs at the beginning our sample (1960). At the beginning, calculated TFP for California and Florida was virtually identical at .8643 and .8649 (base year 1996), respectively. Arizona at .7057 and Iowa at .6733 fell somewhat further behind these two leaders. At the end of the sample, California's measured TFP was approximately 1.8 while Florida's stood at 1.63 after having peaked at 1.79 in 2001. Iowa's measured TFP was 1.5297 which tied it with Illinois for third highest. Arizona's TFP stood at 1.38 and (11th overall), and Texas had fallen to 43rd (falling from 24th in 1960) in terms of measured TFP by 2004.

Early in the sample, Arizona was both highly efficient, well adapted to the technical environment, and highly productive. At the end of the sample, it remained well adapted to the changing technical environment, but its position as a productivity leader had clearly eroded. Rhode Island, on the other hand, stood 35th in terms of productivity in 1960 but had risen to 8th in 2004. So where it once was an also-ran in terms of TFP, it was emerging as a productivity leader by the end of the sample. Nevertheless, because of its very small geographical size, its continued presence at or near the frontier may seem unusual. One interpretation is that smallness is mainly attributable to its small agricultural "plant size" and not to the inefficiency with which it conducts its agricultural industry. Regardless, Rhode Island's agricultural operation is so tiny relative to the rest of US

[10] Alaska, which is not in our sample, has an even smaller agricultural sector.

agriculture, approximately .01% of total production value, that developments in that state cannot reasonably be interpreted as driving developments for production agriculture.

Figure 4 depicts smoothed kernel density estimates for computed efficiency scores for the two sub periods. The 1961-1974 distribution is clearly bimodal. Efficiency scores are concentrated both in the neighborhood of 1 and slightly below the sample mean of approximately .71. The 1991-2004 distribution is also bimodal but appears to have shifted to the left, the new mean is approximately .68 and less mass is concentrated in the neighborhood of 1 and more mass is concentrated in the very low efficiency scores.

This bimodality is evocative of a relatively small "breakaway pack" of innovative and technically efficient states followed by a much larger "peloton" of less innovative and less efficient states. It suggests that the breakaway pack forges the main technical innovations that advance the productivity frontier to which the larger peloton adapts. The perceived loss of mass in the neighborhood of 1 suggests that US agricultural innovation became increasingly concentrated between 1961-1974 and 1991-2004. Fewer states were performing in a manner that could be perceived as well adapted to the operating environment, and an increasing number of states were exhibiting technical operations that would be classed as poorly adapted to the operating environment.

There are different possible explanations. One is that innovative states make innovations that are peculiarly appropriate and increasingly specialized for their agricultures. Such innovations may not spillover immediately into other states. The perceived shift towards a smaller breakaway pack could signal that as agricultural technologies become increasingly refined, innovations become increasingly specific to the commodities for which they are targeted. For example, innovations made in the mechanical harvesting of tree crops, such as almonds, likely have little or no spillover effects for row agriculture. Conversely, improvements in procedures for the planting and tilling of row crops may bring few benefits to producers of tree crops.

Another relates to what measured "efficiency" captures. It measures distance to a common frontier constructed by enveloping the observed data. That frontier rationalizes observed input-output combinations under a set of regularity conditions placed on the underlying hypothetical technology. Consequently, measured inefficiency can have other explanations besides simple economic incompetence. It also reflects lags involved in adapting or adopting technical improvements made in one state to the needs and capabilities of other states with similar agricultural plants. Beyond that measured inefficiency undoubtedly also incorporates elements of heterogeneity that would be relegated to an error term in an econometric framework. And some of these may have little to do directly with the underlying technology, particularly if they reflect institutional or regulatory differences between states. Thus, another interpretation is that the perceived shift in the efficiency distribution is a consequence of US agriculture becoming increasingly heterogeneous and, possibly, increasingly specialized.

Similar observations elsewhere have inspired a vast literature that uses a two-stage procedure to estimate and then explain measured inefficiency. In the first stage, data envelopment procedures are used to measure inefficiency, and in the second stage measured inefficiency is regressed upon a set of explanatory variables. Simar and Wilson (2007) both review and propose an alternative approach to this literature. Because our intent is not to explain the potential sources of inefficiency, we make no attempt to undertake a detailed econometric investigation of measured efficiency. Still, one cannot help but notice that both the moisture variate and the temperature variate also exhibit bimodality over these periods (Figure 5). The hypothesis that some of this measured inefficiency is attributable to changing weather patterns seems natural.

To investigate this potential relation, we estimated three different bias-corrected regression models relating measured efficiency to our temperature and moisture variates. One model was estimated for the whole sample period (1961-2004), and one each for the two sub-periods. The bias-corrected regression procedure is due to Kneip, Simar, and Wilson (2015).[11] Results are reported in Table 2.

Overall, the weather variates explain only a tiny percentage of measured inefficiency. Thus, the bulk of this measured inefficiency seems attributable to other sources of heterogeneity. Nonetheless, the estimated coefficients in each case appear to be significantly different from zero at all traditional levels of significance and suggest that measured efficiency is positively correlated with the moisture variate but negatively correlated with the temperature variate.

From these results, we can infer that relatively fewer states are well adapted to low-moisture operating conditions than ones that are well-adapted to higher-moisture operating conditions. For example, one might expect states operating in chronically arid environments to have arranged quasi-fixed-input infrastructure to permit relatively productive operation even when rainfall is low. Such infrastructural arrangements might include investment in surface irrigation and pumping facilities (Schlenker, Hanemann, and Fisher 2005). On the other hand, states that typically operate in more moist conditions, may find it very difficult to make short-run adjustments to drought-induced lack of rainfall. The short-run empirical consequence might be a perceived drop in measured efficiency relative to the enveloping production frontier. And when production conditions returned to more normal moisture levels, that short-run measured inefficiency might disappear.

These results also suggest that measured inefficiency is higher when temperatures approach extreme levels. Again one plausible inference is that relatively few states have agricultural plants that are well adapted to operating at extreme temperatures. Thus, few states will operate near the production-frontier envelope for those higher temperatures. And when other states are exposed to such extreme temperatures as a result of variability in their weather patterns, short-run adjustments

[11] The bias correction is needed to correct for the manner in which the efficiency scores are generated and their one-sided nature (Kneip, Simar, and Wilson 2015). The procedure relies on a jackknife bias correction. The jackknife bias correction is calculated by averaging over independent estimators, obtained from independent subsets of the original sample. The original sample is split into two subsamples by dividing the states in two groups. All observations relative to a state are all in one of the two subsamples. The efficiency calculation is repeated in each subset separately and two associated regression estimates are obtained. The jackknife bias estimate is obtained by averaging these estimates. This bias estimate is used to correct the original regression estimate.

are difficult to make and the empirical result is relatively large measured inefficiencies. On the other hand, more states appear to be well adapted to lower or more moderate temperature patterns and thus will tend to operate closer to the boundary of the production frontier when those weather conditions occur.

3.2 The Observed Components of Agricultural TFP Growth

Our productivity growth calculations were carried out for 14 30-year periods (1961-1991, 1962-1992,..., 1974-2004). TFP change and its components were calculated for each of these 30-year time periods for each of the 48 states in the sample.[12]

Figure 6 presents smoothed kernel density estimates for TFP change and each of its four components. Over the 48 contiguous states, the 30-year period TFP growth rates averaged approximately 49.6% suggesting that the average state could get approximately 1.5 times more output from the same input base in, for example, 1991 than it could in 1961. As is evidenced by panel a in Figure 6, productivity growth appears unimodal around the observed mean with a calculated kurtosis of 3.0504.

Turning to the components of that TFP change, one sees quite different patterns emerge for each component. The observed distributions for $X\Delta$ and $W\Delta$ appear quite leptokurtic around means of approximately .2% and -1.3% suggesting that, on average, neither contributed significantly to average TFP growth. The calculated kernel density for $W\Delta$ appears to be unimodal around its mean, while the calculated kernel density for $X\Delta$ contains a hint of bimodality with some mass concentrated slightly above the mean. Calculated kurtosis for $W\Delta$ is 15.4535, while calculated kurtosis for $X\Delta$ is 9.7210.

Because weather effects are stochastic and beyond the control of the individual producer, observing that $W\Delta$ contributed relatively little to average productivity growth is not surprising. One naturally expects relatively good and bad growing conditions to balance one another. Recalling that $X\Delta$ accounts for scale-related differences associated with the differing input bundles between the two time periods, the evidence suggests that the effect on observed TFP change over the 30 year periods was negligible.

Both calculated $E\Delta$ and $T\Delta$ measures have more platykurtic calculated kernel densities than either $X\Delta$ and $W\Delta$ as is evidenced by a calculated kurtosis for $E\Delta$ of 5.0403 and for $T\Delta$ of 6.7822. The $E\Delta$ distribution is centered around a mean of -4.3% suggesting that over these 30 year periods, the average state struggled to adapt to the evolving productivity frontier. Moreover, the lower tail of the $E\Delta$ distribution appears to be slightly thicker than its upper tail. This is not inconsistent with the evidence reported in Figure 4 and suggests that the more innovative states are gradually pulling away from the less innovative states. It conveys the sense that an increasing number of states were failing to adapt to the ever-changing production environment at the end of this thirty-year periods.

[12] A more complete summary of those results is available from the authors upon request.

Again an obvious suspect for this struggle to adapt is weather. As noted, the directly calculated $W\Delta's$ effects are quite small. But the results in Table 2 suggest that efficiency levels are positively correlated with the moisture variate and negatively correlated with the temperature variate. Naturally, $E\Delta$, being derived from levels, would manifest a similar tendency. That implies that a movement towards higher moisture levels, as has occurred, would push in the direction of more efficient production, a positive adaptation. On the other hand, the results in Table 2 also suggest that the general trend to warmer temperatures might retard adaptation to the changing technical frontier. Hence, there appears to be the potential for changing weather patterns to have a pull-push effect on the rate at which states adapt to changing technical possibilities.

The calculated kernel densities for $T\Delta$ give slight evidence of bimodality with mass concentrated near the calculated mean of 54.9% and around 63-65% hinting at a "twin peak" phenomenon characterized by a group of more rapidly innovating states diverging from less rapidly innovating states. The overall picture that emerges is one of technical innovation outpacing observed TFP growth by approximately 5% over the 30 year periods with efficiency loss (failure to adapt or adopt) accounting for the bulk of the difference and weather being a slightly more important determinant (again negative) of average TFP growth than input adjustments, but only marginally so.

Table 3 reports information on the average components of TFP change for these 14 30-year periods for 21 states. There are four groupings of states. The first grouping consists of 7 states that were leaders in terms of observed TFP at the beginning of our sample (1960) or at the end of the sample (2004). The second group consists of TFP laggards at the beginning of the sample (1960) or at the end of the sample (2004). The third group consists of states having the highest average TFP growth between 1960 and 2004 (as calculated by USDA) and the final group consists of those states having the slowest average TFP growth between 1960 and 2004 (as calculated by USDA). There is some overlap between groups and so some states appear in more than one group.

For each state, their TFP rank in 1960 and 2004, their average (over the 14 separate 30-year periods) $TFP\Delta$ score (not to be confused with the 1960-2004 change), their average $E\Delta$ score, their average $T\Delta$ score, their average $X\Delta$ score, and their average $W\Delta$ score are all reported. The final column in Table 3 reports calculated values for the observed coefficient of variation (in absolute value terms) for the $W\Delta$ scores. Entries followed by a diamond, ⧫, indicate calculated average scores taken over observations where infeasible calculations were reported. (Averages reflect averages only on feasible scores in these instances. Thus, if there were 13 feasible scores and 1 infeasible score the weighting factor for each observed score was $\frac{1}{13}$.)

A later section considers the infeasible calculations in more detail. But glancing at Table 3, one cannot help but notice that more instances of calculated infeasibilities for $W\Delta$ are encountered in the first group, the leading TFP states (five of the seven entries), than in any of the other groupings. This suggests, as we indicated earlier, that these states who operated in the neighborhood of the technical frontier in the 1960s likely encountered weather conditions in the 1990s that were outside the realm of experience in the earlier part of the century.

Looking at the first group, one sees that in 1960 the states with the highest observed TFP were, in order, Florida, California, Arizona, Iowa, and Alabama. As already noted, Florida and California had virtually identical TFP scores in 1960 while Arizona, Iowa, and Alabama fell somewhat further behind. By 2004, California and Florida had switched places, Iowa was now third and virtually tied with Illinois and Delaware had moved into fifth position from 6th in 1960. Meanwhile, Arizona and Alabama had fallen to 11th and 8th, respectively.

Several characteristics of the changes for Arizona and Alabama, the states that fell out of the top 5, are to be remarked. First, these states are in different regions of the country and have different agricultures. As noted, Arizona's livestock industry is concentrated in cattle and calves while Alabama's livestock production, which accounts for about 70-80% of its production value, is heavily concentrated in poultry. The calculated average $T\Delta$ scores for both of these states is below the national average of 54.9%. Alabama's, at 51.4% is about 3.5 points below the national average, and Arizona's, at roughly 40%, is almost 15 points below the national average. The precise cause of Arizona's relatively slow rate of technical change cannot be determined from our data. But Arizona clearly operated in a neighborhood of the frontier that was moving less quickly than more rapidly developing neighborhoods. Its average $E\Delta$ score of about 1.5 indicates that it had moved closer to the technical frontier in the 1990s than it had been in the 1960s and 1970s. Alabama, on the other hand, realized an average $T\Delta$ score that was closer to the national average, but its average efficiency change score was approximately -8.5 percent. Technical improvements were available to Alabama, but the state was not able to incorporate these technical improvements effectively into its production practices as it fell behind the advancing frontier. Neither Alabama nor Arizona had relatively large $X\Delta$ scores. Both were indicative of a negative scale effect, Alabama's was almost imperceptible while Arizona's was larger at approximately -1.9%. Both states had average $W\Delta$ scores that were approximately zero (not unexpected), and both experienced relatively more variability (as measured by the coefficient of variation) than all of the leading TFP states except for Florida. Moreover, both experienced instances of infeasibilities suggesting that the production conditions, including weather, that they encountered in the 1990s were outside the range of technical experience in the earlier part of our sample. Thus, while the average effect of weather on their calculated TFP growth seems to be relatively small, clear evidence also exists that both states experienced somewhat different production conditions at the end of the century than at the middle part of the century.

The two states that moved into the leading TFP group at the end of our sample period (Delaware and Illinois) are quite dissimilar in size and in composition of their agricultural industries. Delaware is heavily concentrated in broiler production with a relatively sizable concentration of grains and oilseeds that support the broiler industry. Illinois's primary production commodities are grains and oilseeds and their main livestock industry is hog and pig production. Both states apparently experienced worse operating weather conditions, on average, in the 1991-2004 era than in the 1961-1974 era. Delaware's $W\Delta$ score averaged -3.77% and Illinois's $W\Delta$ score averaged -2.05%. Because broiler production involves containment of the animals, the relatively large negative weather effect for Delaware may seem paradoxical at first glance. However, it must be remembered that TFP accounts for both outputs and inputs. And thus, the observed warming of weather required larger expenditures on climate control and disease control and helped retard TFP growth. As indirect evidence of this effect, we note that for the 1990-2000 decade, the use of energy inputs by Delaware agriculture grew at an average annual rate of 4.98%, which was the highest observed across the 48 contiguous states (New Mexico's was second at 2.85%).

Over the 14 30-year periods, Illinois's average TFP growth rate was very close to the national average of 49%. Delawares was considerably lower at 42.9. Part of Illinois's quicker growth is explained by it experiencing a more rapid rate of technical change, 58.4%, than Delaware, 48.2%. The former was about 3.5 points higher than the national average and the latter was about 6 points below the national average. Interestingly, despite moving into the top 5 in terms of TFP, neither of these states kept pace with the advancing technical frontier. Both experienced average $E\Delta$ scores of approximately -11%. Delaware and Illinois differed dramatically in their size adjustments, Delaware had an average $X\Delta$ of 13% suggesting that it successfully exploited available economies of scale for x during these three decades. Illinois also experienced increasing frontier returns, but at a much lower level of approximately 4%. The picture that emerges is of two states struggling to adapt to the advancing technical frontier. One state, Delaware, compensates by more effective exploitation of economies of scale, while the other, Illinois, benefits from a much more rapid rate of technical change. And, in both instances, weather related changes dampened productivity growth perceptibly.

The three states that appeared in the top five both at the beginning of our sample and at the end of our sample, Florida, California, and Iowa are from very disparate regions of the country. Two of these states, California and Iowa are the top agricultural producing states in the United States. In 2012, with $42.6 billion in agricultural production value, California ranked first overall, first in crop production, and third in livestock production. Iowa, with $30.8 billion in production value, ranked second overall, second in crop production, and second in livestock production (behind Texas). Florida, known for its relatively temperate climate and orange production (in which it ranks first), is a moderately-sized agricultural state that falls just outside the top 20 in terms of total production value.

Their observed patterns of TFP growth over the 14 30-year time periods, however, are quite different. California experienced extremely rapid technical change that averaged 65%, approximately 11 percentage points higher than the national average. It remained almost continuously on the production frontier as its $E\Delta$ score was less than .8%. Thus, any reasonable interpretation of the data suggests that it was directly responsible for many of the technical innovations that pushed the technical frontier outward during that 30 year period. Its average $W\Delta$ score was 1.5% with a coefficient of variation of 6.0 suggesting that weather, on average, was slightly better in production terms in the 1991-2004 period than earlier and more variable than many states experienced, but still relatively minor.

The greatest drag on California's productivity growth was its large (in absolute value terms) and negative $X\Delta$. In each of the 14 30-year periods, its $X\Delta$ score was negative, and it averaged -16%. Given its extremely large magnitude and the fact that California is virtually always on the frontier, this effect requires further comment. Recall that the index measure is

$$\left(\frac{f_0\left(x_t, w_0\right)/x_t}{f_0\left(x_0, w_0\right)/x_0}\right)^{\frac{1}{2}}\left(\frac{f_t\left(x_t, w_0\right)/x_t}{f_t\left(x_0, w_0\right)/x_0}\right)^{\frac{1}{2}},$$

which gives California's average product for x_t and x_0 as measured relative to technology 0 and t. There is thus a strong indication that aggregate input growth over these 30-year periods outstripped *maximal output* growth. In 1960, the index of California aggregate input stood at 3.8835 (base is Alabama in 1996). In 2004, it measured 5.0492, a roughly 30% increase. Our 30-year results suggest that the associated growth in maximal output was considerably lower. This served as an effective brake on California's TFP growth despite its ability to make very rapid and significant technical advances.

Iowa, on the other hand, experienced a much lower rate of technical change at 49%, about 5 percentage points below the national average. However, in each of the 14 30-year time periods, its $X\Delta$ score was positive and averaged 8% overall indicating that it successfully exploited available economies associated with x over the 30 time horizons. This adjustment was associated with a downsizing of its "agricultural plant size". In 1960, its input index stood at 4.2611 and by 2004 that had fallen to 3.3940. This observed input adjustment corresponds nicely with the "farm problem" as it was perceived at the beginning of our sample. In the Kennedy era, the practical policy problem for most of US agriculture was one of overproduction and "getting excess resources out of agriculture" (Hillman 2011). The evidence suggests that Iowa made this adjustment effectively. The ultimate consequence was its ability to maintain its role as an agricultural TFP leader despite experiencing a relatively low rate of measured technical change.

Thus, where California relied on rapid technical change but seemingly allowed its plant size to grow too quickly, Iowa streamlined its agricultural operations to maintain a high rate of productivity. While it is highly problematic to draw precise inferences from such aggregate data, one is tempted to suggest that California's experience may be indicative of extreme "research" success but modest "educative" success. Iowa's experience, on the other hand, might be indicative of "educative" success but more modest "research" success. Given the nature of the data and the clear lack of an explanatory model, it's misleading to speak of "reasoning" here. But the heuristic is that prior to 1960, Iowa may have overexpanded its "plant size". Eventually it adjusted by moving resources out of agriculture. The exact process, of course, is something this study can say nothing about. Clearly, competitive pressures were in play. On the other hand, technological advances seemed to have been so rapid in California that they supplanted the need for some of its agricultural "capacity" as measured by x.

Unlike California, Iowa tended to fall behind the advancing technical frontier. Its average $E\Delta$ score was -4.4% (approximately the same as the national average) suggesting that it was further from the efficient frontier in the 1990s than it had been in the 1960s. Its average $W\Delta$ score was -2.5% with a coefficient of variation of 3.5%. Iowa's weather patterns, as measured in production terms, were slightly less variable than experienced by California. And, unlike California, Iowa experienced one instance (1963-1993 comparison) of an "infeasibility" in its $W\Delta$ calculation indicating that it experienced production circumstances in 1993 that were outside the range of relevant production experience in 1963. (More on this later.)

The characteristic that most distinguishes Florida's TFP growth pattern from those of California and Iowa is its $W\Delta$ score. Although, the average score is quite small, the coefficient of variation at 28.6 is the largest reported in Table 3. Moreover, of the 14 30-year time periods, half were characterized by $W\Delta$ infeasibilities indicating that Florida in the 1991-2004 period was operating under quite different circumstances in terms of its input base than in 1961-1974. Florida was almost exactly the "average" US state in terms of its observed $T\Delta$ score. Moreover, it remained almost continuously on the technical frontier suggesting that its innovations, rather than those of others, helped drive the placement of the frontier. The latter observation is particularly important in light of the large number of observed infeasibilities. The operating conditions at the portion of the frontier relevant for Florida in both the 1961-1974 period and the 1991-2004 were Florida's.

Turning to the TFP laggards, first consider Louisiana. Although we report evidence on that state's TFP decompositions, we emphasize that the tabulated evidence for that state, apart from the $E\Delta$, is borderline noninformative. The average reported is for a single observation, a direct manifestations of "infeasiblities" for Louisiana's 1991-2004 input combinations relative to the earlier relevant technology (more on this later). Thus, all that can be said with confidence is that Louisiana, whose 1960 TFP ranked 44th, had improved its TFP ranking to 37th for 2004. And, on average, in the 1991-2004 period it operated closer to the frontier than in the earlier period.

Looking at the TFP laggard group, we next focus on Oregon and Michigan. Casting either as "laggard" is problematic semantically. While both were TFP laggards in 1960, they had long shriven that mantle by 2004. Over the intervening four decades, Oregon's annual average growth rate was the highest and Michigan's was third highest with Rhode Island falling second.

For our three-decade periods, Oregon's average rate of TFP change was 65% placing it 16 points higher than the national average. That rapid growth rate was a combination of a slightly below average $T\Delta$ effect (53%), a steady process of positive adaptation to new technologies (11% average $E\Delta$), and very minor $x-$size effects, $X\Delta$, and weather effects. Michigan's average rate of TFP change for those three decades was 71%. That rapid growth rate was a combination of a higher than average $T\Delta$ (58%), a steady movement towards the technical frontier (11% average $E\Delta$), a positive $X\Delta$ effect (5%), and a small, but perceptible, weather component (-3% average $W\Delta$). The latter suggests that Michigan was forced to cope with more negative weather conditions in 1991-2004 than in the earlier periods.

Looking at the "other TFP laggards" reveals a distinct pattern: slow $TFP\Delta$ associated with states failing to keep pace with the evolving technical frontier ($E\Delta$ quite negative). In the main, none of these laggard states experienced overly slow measured rates of technical change or much poorer weather operating conditions. Rather frontier opportunities seemed available, but these states were simply not capable of taking advantage of them. As already mentioned, other factors beyond increasing technical incompetence may be at play. For example, these measures might reflect institutional disparities across different states that prevent technology developed in one setting being transferrable to others, so that the "measured" $T\Delta$ may be a misleading indicator of availability of technical opportunities. Regardless of whether that is true and the effect represents continued incompetence, what is undeniable is that these laggard states were incapable of keeping pace agriculturally with other states. The anemic performances of Oklahoma and Wyoming are particularly to be remarked. Both states had average $TFP\Delta$ scores of less than 30% for these three decades while both experienced average $E\Delta$ scores well smaller than -20%. Where Oklahoma was a relative TFP leader in 1960 (at number 13), it was racing to the bottom in these 30-year period and had become an agricultural also-ran by 2004.

Examining the decompositions of $TFP\Delta$ for the remaining states in Table 3 reveals a very clear pattern. None of the fastest or the slowest growing states experienced infeasibilities between the two periods. This suggests, at least in terms of observed weather patterns, that these states experienced weather patterns in the latter period that were relatively similar to those present in the first period. With the exception of Colorado, the coefficient of variation for their $W\Delta$ scores were below the national average indicative of relatively modulated weather patterns, at least as measured by agricultural production effects. Several of the fastest growing states experienced perceptible average $W\Delta$ effects. Indiana experienced a higher than average (in absolute value terms) negative weather impact of approximately -3%. On the other hand, Massachussetts average $W\Delta$ effect was strongly positive at approximately 7% and helped offset its negative size adjustment.

For most of the fastest-growing or slowest-growing states, the bulk of observed $TFP\Delta$ can be attributed to either $T\Delta$ or $E\Delta$. Thus, the fastest growing states tended to experience quite rapid technical change or to catch up with the technical frontier. On the other hand, the slowest growing states typically experienced slightly above average to slightly below average $T\Delta$ but tended to plunge away from the technical frontier as their $E\Delta$ scores fell well below the national average.

A clear message that emerges from Table 3 is that in terms of average $TFP\Delta$, most of the growth that emerges or that fails to emerge can be attributed to either technical change, as measured by $T\Delta$, and either successful adoption of available technical improvements or failure to adopt available technical improvements as measured by $E\Delta$. $W\Delta$ is important for some states, but on average its overall effect is relatively small. The same is true for $X\Delta$. And, in particular, it seems clear that negative weather effects did not play a prominent role in contributing to poor TFP growth over the long term in the slowest productivity-growing states. In short, slow growth is attributable to either a failure to innovate or a failure to adapt innovations.

3.3 Weather and the Distribution of TFP Growth

To gauge further the overall contribution that $W\Delta$ makes to agricultural TFP growth, we have performed counterfactual experiments similar to ones employed by Kumar and Russell (2002) and Henderson and Russell (2005). A key goal is to determine whether observed TFP growth can be adequately explained by $T\Delta$, $E\Delta$, and $X\Delta$ without resorting to $W\Delta$. The results summarized in Table 3 seem to suggest that this may be true but more can be said by looking at the entire distribution of $TFP\Delta$ and its component parts.

Thus, for each state for each year between 1961 and 1974, we have taken state-level TFP and multiplied it successively by one plus its measured 30-year percentage technical change, by one plus its 30-year efficiency change, and by one plus its 30 year $X\Delta$ score to arrive at *a hypothetical TFP that would have occurred in the absence of* $W\Delta$ *over the 30 years.* This was done in stages, adding in first the 30-year technical change, then the 30-year efficiency change, and then the 30-year input change. We also performed a similar experiment to determine whether $T\Delta$, $E\Delta$, and $W\Delta$ together could account for observed productivity change without the presence of $X\Delta$. At each stage, we conducted a nonparametric test of equality of the resulting hypothetical distribution with the true TFP distribution for 1991-2004 (Li, Maasoumi, Racine 2009).[13]

The hypothesis test results are summarized in Table 4 and the results are illustrated graphically in Figures 7 and 8. The null hypothesis for Table 4 and the figures is that the observed distribution for TFP and the hypothetical distributions are the same. As both the table and the figures illustrate, this null hypothesis is rejected at all traditional levels of significance when the hypothetical distribution only includes $T\Delta$. Differences remain to be explained. When $E\Delta$ is introduced, it is no longer possible to reject the null hypotheses at traditional levels of significance. Thus, as a practical matter, strong statistical discrimination between the observed TFP distribution and the hypothetical distributions created by including $T\Delta$ and $E\Delta$ is not possible. Once again, the data seem to suggest that in terms of aggregate behavior, the primary drivers of productivity change are the abilities to innovate and to adapt to those innovations and not weather or size effects.

3.4 Infeasibilities and Indexing Weather

Recall that the weather index,

$$\left(\frac{f_0(x_t, w_t)\, f_t(x_t, w_t)}{f_0(x_t, w_0)\, f_t(x_t, w_0)}\right)^{\frac{1}{2}},$$

is a cardinal index, measured in units of aggregate agricultural output, of the production effects of (w_t, w_0) holding aggregate input at x_t measured using the 0 technology and the t technology. If this index is poorly defined, it communicates information about the technical feasibility of w_t and w_0 that is available from our conservative approximation to the underlying aggregate technology. By the manner in which that approximation is developed, the component of the index defined relative

[13] Similar results were obtained using a Kolmogorov-Smirnov test, and these are available from the authors upon request.

to the t technology, $\frac{f_t(x_t,w_t)}{f_t(x_t,w_0)}$ is always well defined. Thus, if an infeasibility occurs, it will be in the component defined relative to the 0 technology, which in our case refers the technology that existed in the 1961-1974 sub period.

We focus on the experience of 4 states: Arizona, Florida, Iowa, and Louisiana. Three of these states (Arizona, Florida, and Louisiana) experienced large numbers of infeasibilities. Three of these states routinely perform very close to the frontier (Arizona, Florida, and Iowa). One state (Arizona) moved from being a relatively top-ranked state in terms of productivity to a lower ranking, two (Florida and Iowa) did not, and one (Louisiana) was a relatively low-ranked state in productivity terms for both periods.

Table 5 tabulates the years for which an infeasibility occurred. In every instance, the infeasibilities occurred because we could not calculate $f_0(x_t, w_t)$. Given that we have maintained free disposability of x, this is not unexpected. Thus, the infeasibilities emerge from two sources: not imposing free disposability on w and the fact that the weather variates in 1991-2004, were more extreme than in 1961-1974. Producers faced different productive conditions in the latter period than in the former. The fact that production continued in the second period implies that producers adapted to these more extreme conditions in some fashion. A closer glimpse of how they adapted can be gleaned from examining their relative experience.

Arizona and Florida experienced warmer operating conditions in 1991-2004. At the same time Florida was quite wet, while Arizona experienced low humidity. As a consequence, $f_0(x_t, w_t)$ was often not producible using our conservative approximation to the technology. This happened to Florida in 1991, 1994,1995, 1997, 1998, 2002, and 2003 and to Arizona in 1992, 1994, 1996, 1997, 2000, 2001, 2002, 2003, and 2004. During both the latter period and the former period, both states stayed relatively close to the technical frontier, suggesting that they were doing the *best that was observed*. Whether this was the best that was possible is something our analysis cannot determine. Florida remained one of the top performers in TFP terms, although its TFP was quite variable. Its productivity actually peaked at 1.79 in 2001 before falling back to its ending level in 2004. Arizona, on the other hand, tumbled from third in the 1960 TFP rankings to eleventh (1.38) at the end of the sample. Thus, evidence suggests the combination of increased heat stress and low humidity were an important drag on Arizona's TFP performance relative to that of Florida.

Louisiana experienced higher humidity in the latter period. Relative to what occurred in 1961-2004, these conditions were so extreme that the weather index could be computed in only one year. And for that instance, the computed effect was quite negative. Louisiana was somewhat of a TFP also-ran in 1960 and largely remained one.

That brings us to Iowa. Its sole infeasibility occurred in 1993. That summer massive flooding in Iowa caused at least 17 fatalities and over $2 billion in damages. In some areas of the state, it rained 130 consecutive days and flooding occurred multiple times. The experience was so significant that Iowa Homeland Security and Management has called it "...one of the most defining natural disaster incidents in Iowa history". The agricultural response was a massive drop in yields. But as already noted, after its recovery, Iowa remained a TFP leader at the end of our sample period.

4 Concluding Remarks

Methods for approximating the aggregate stochastic agricultural technology that incorporate weather elements directly into the approximation were developed. Using the aggregate technology as the reference base, the traditional measure of agricultural TFP growth was decomposed into four components (weather, technological change, efficiency, and input). Using the USDA state-level TFP panel combined with data drawn from Schlenker and Roberts (2008; 2009), decomposition analyses of observed 30 year changes in agricultural TFP for each of the 48 contiguous US states have been performed and analyzed.

Before summarizing results, it is important to emphasize this study's intent. The analysis is not meant to explain what drives TFP growth. That craft is left to others. We do note, however, that its execution typically requires different and more restrictive assumptions than ours. Our goal is more conservative: to examine empirically the different components of observed TFP change. In the end, the intended result is essentially an empirical exercise in blackboard economics. To visualize, draw $f_t(x_t, w)$ on two axes holding x_t constant while varying w. One component of the weather index, $f_t(x_t, w_t) / f_t(x_t, w_0)$, is measured as relative lengths along the horizontal axis. All of the remaining components of our indices are illustrated similarly.

Thus, rather than explaining TFP growth, our intent is to use index procedures to get different empirical snapshots of how agricultural TFP is changing. The basic idea follows Polya's (1945) heuristic for problem solving. Start by identifying what is known and what is unknown. Then determine the question that needs to be answered, what is needed to answer the question, and what constitutes an answer. Our goal is to contribute to the first stage in the process. Before attempting to isolate causal factors, the goal is a more precise understanding of what has actually happened. After that is known more precisely, the proper search for causality can commence.

The results indicate that the pattern of average state-level TFP growth and the distribution of that growth are closely approximated by the patterns of the technical change, $T\Delta$, and efficiency change, $E\Delta$, components of the decomposition. A shift in the frontier of the technology made it possible, on average, to get about 1.54 times as much product in 1991-2004 than was possible in 1961-74. At the same time, $E\Delta$ was negative on average and slowed measured TFP growth. That change was also evocative of a more diffuse efficiency distribution. Fewer states perform in the neighborhood of the technical frontier and more states lag behind. Thus, the observed increased diffusion of state-level TFP (Figure 2) seems mainly comprised of a combination of fewer innovative states and more states struggling to maintain pace with an ever advancing frontier. There is clear evidence of bimodality in the distribution of efficiency with which states exploit the technology. Moreover, that bimodality seems to have shifted towards a lower concentration of technically efficient states and greater concentration of laggard states. Some evidence of the emergence of a "twin peak" phenomenon in technical innovation, $T\Delta$, also exists. In terms of what can be inferred from our data, $W\Delta$ and $X\Delta$ do not appear to have been important components of observed differences in the changes of the distribution of TFP.

In pivoting from an examination of the grouped data to a closer examination of state-level performance, clear differences emerge. Some states have experienced both positive and negative $W\Delta$ effects. A number of states on the technical frontier experienced weather conditions in 1991-2004 that were so different from 1961-1974 that our conservative methodology does not permit calculation of weather-related effects on agricultural TFP in some time periods. Of the three leading TFP states (California, Florida, and Iowa), this indeterminacy was most pronounced for Florida, was not experienced for California, and was experienced only once for Iowa (the result of a massive flood event). Arizona, a TFP leader in 1960, encountered this phenomenon repeatedly as a consequence of increased heat stress in 1991-2004. Having started our sample period (1960) ranked third in observed TFP, it had fallen to eleventh in 2004.

As always, caveats exist and further research is needed. Our analysis is aggregate. And while this has desirable characteristics in terms of providing a broader perspective on "what's going on with agriculture and weather", it has well-known drawbacks. It is not intended to and does not pretend to supplant continued disaggregate analyses. On the other hand, very few truly relevant aggregate conclusions can be drawn from very disaggregate analysis. Moving from the highly disaggregate to the aggregate requires well-defined and conceptually consistent aggregation schemes. Even though it is not simply a matter of "adding up effects", an inescapable reality is that most "aggregation" schemes eventually require summing somewhere in the procedure. Once imposed anywhere in the scheme, it has been well-known since the time of Gorman (1953, 1968) that some form linearity elsewhere is a prerequisite for consistent aggregability. And in that regard, weather promises to be particularly problematic because its potential impacts on agricultural systems are likely quite nonlinear. And so, for example, knowing what's happening in Montgomery County, Maryland weather may not prove particularly informative nationally. And knowing what's going on at the farm or field level is potentially even less informative.

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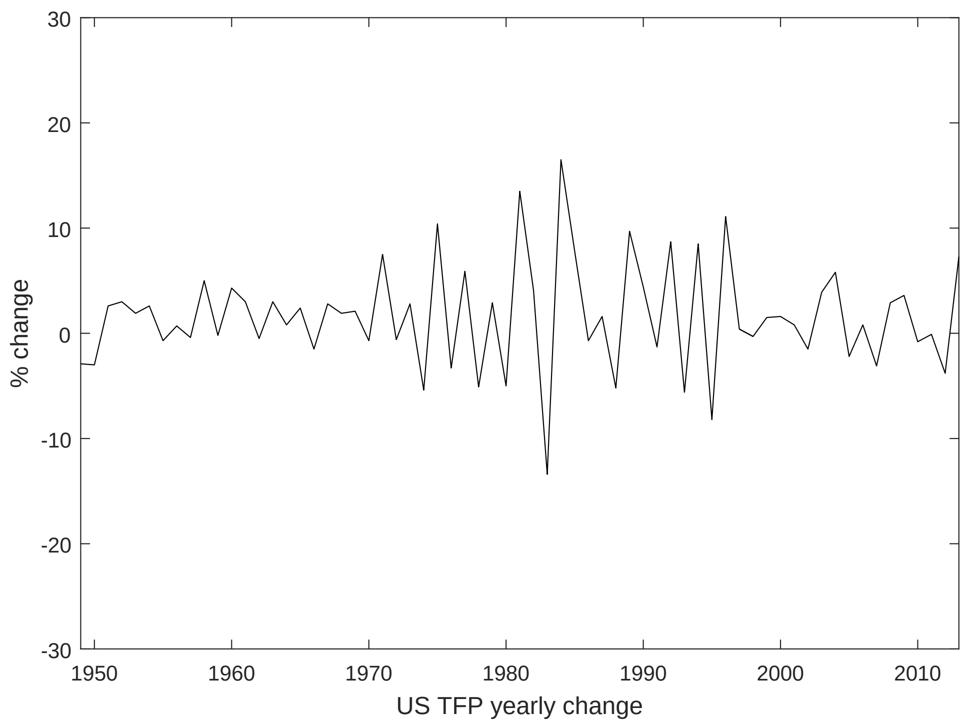


Figure 1: Annual growth rates of total factor productivity, U.S. agriculture, 1949-2013

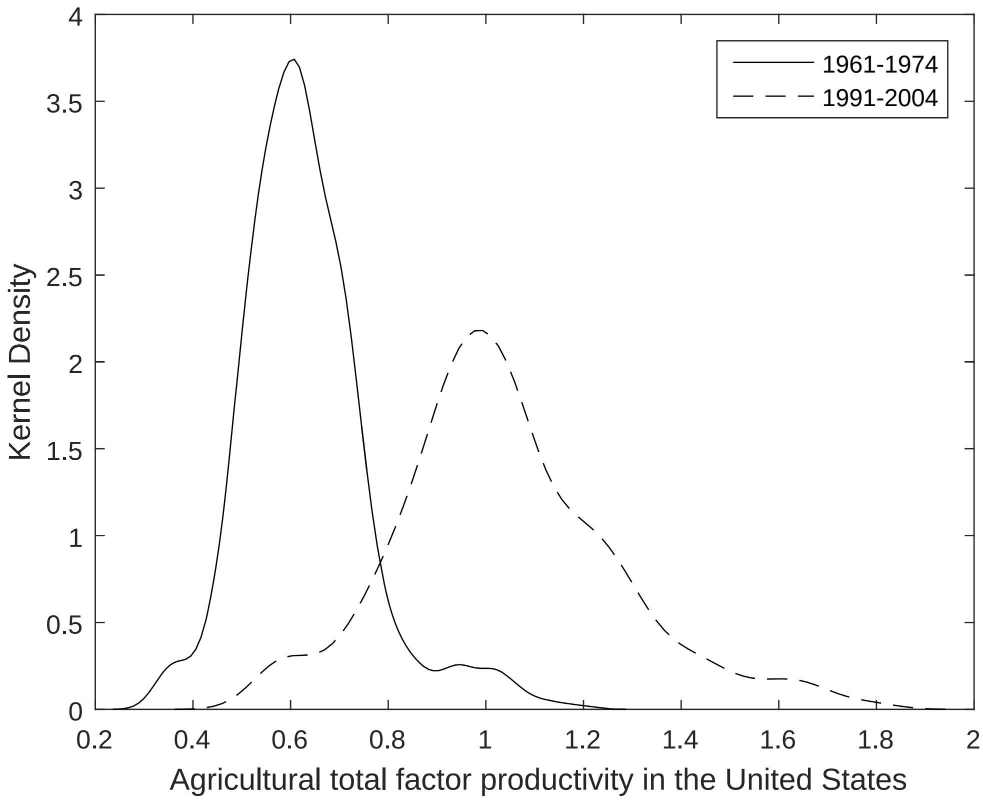
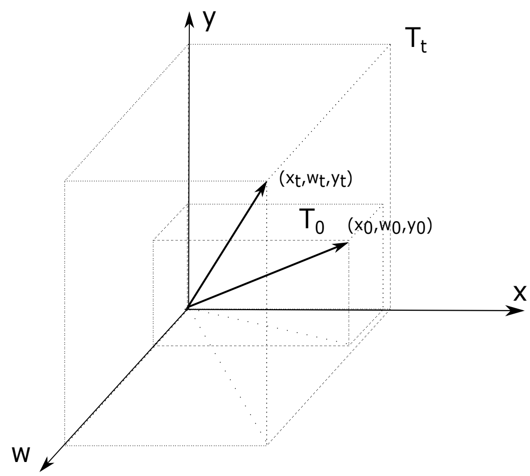
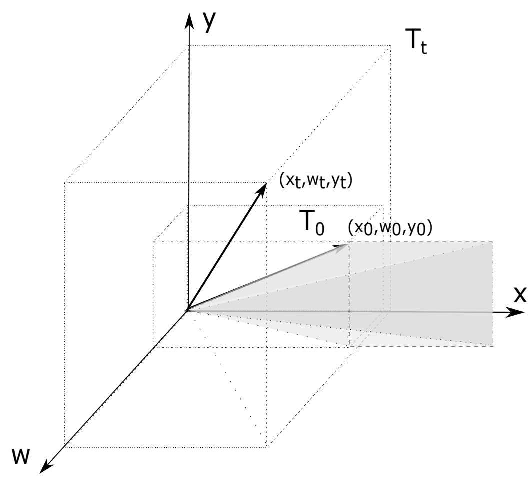


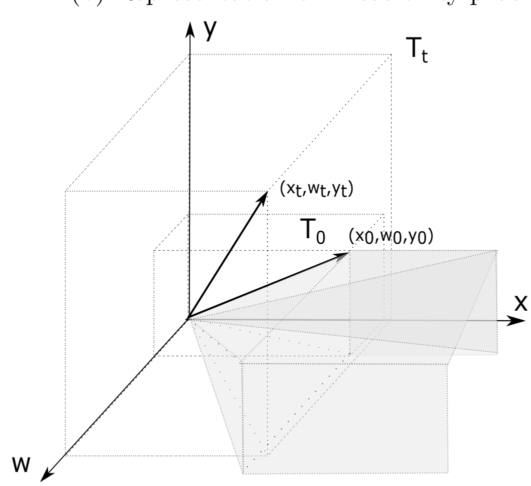
Figure 2: Kernel Densities of observed state-level total factor productivity, comparison 1991-2004 and 1961-1974



(a) Representation of input and outputs combinations



(b) Representation of infeasibility problem



(c) Solution to infeasibility problem

Figure 3: The infeasibility problem given two combinations of inputs and output for one state at different time periods

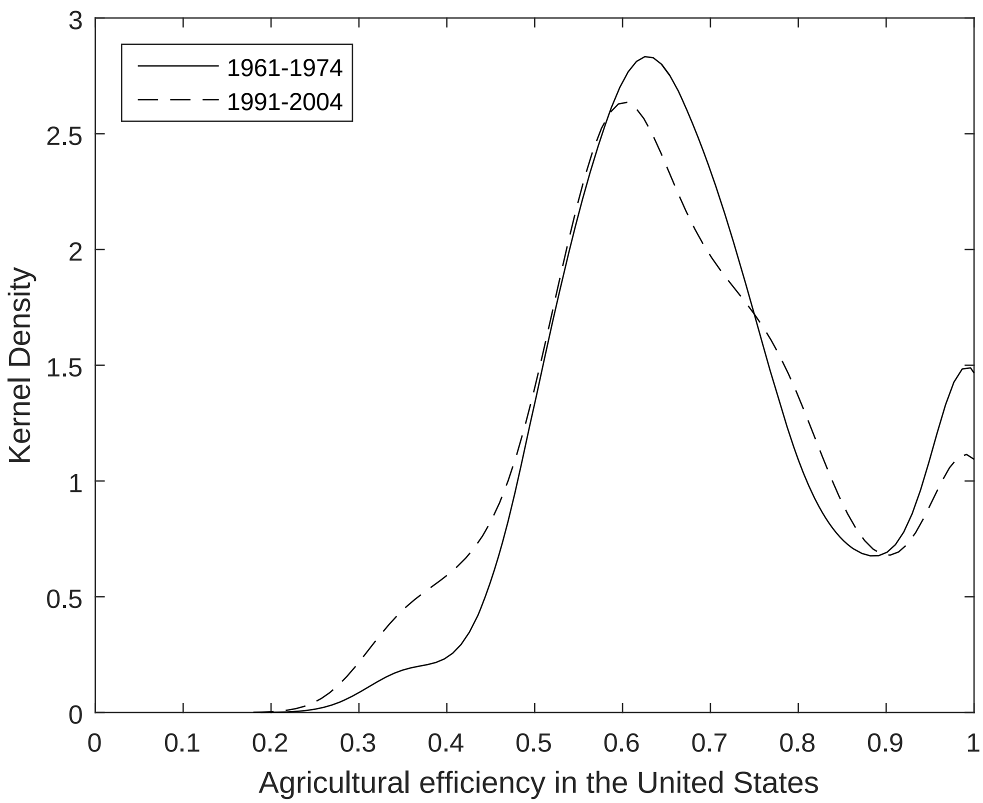


Figure 4: Smoothed kernel densities of efficiency scores, comparison 1991-2004 and 1961-1974

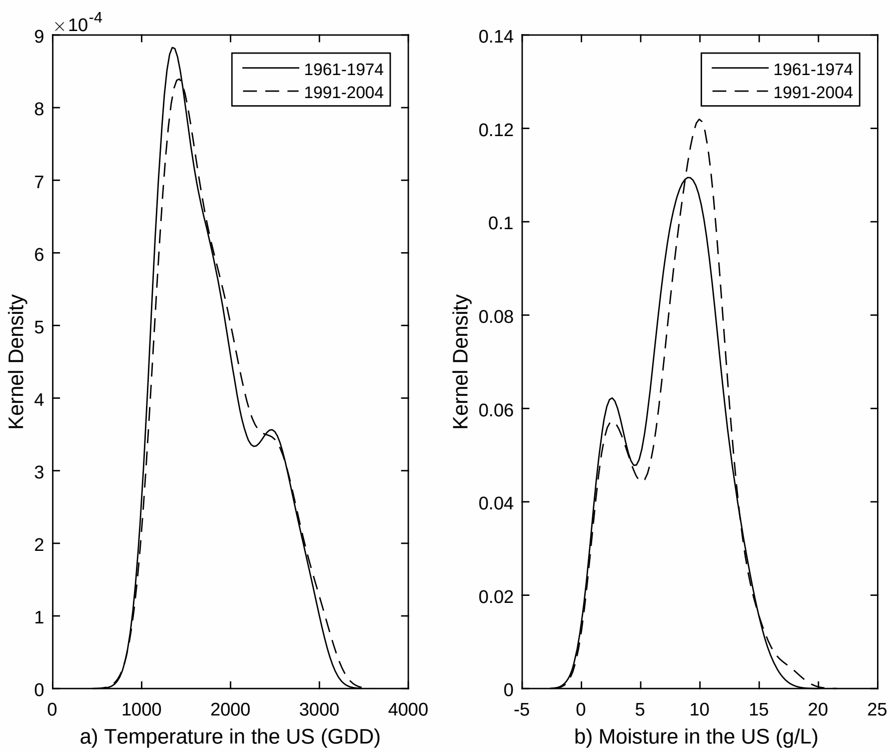


Figure 5: Kernel densities of temperature and moisture, comparison 1991-2004 and 1961-1974

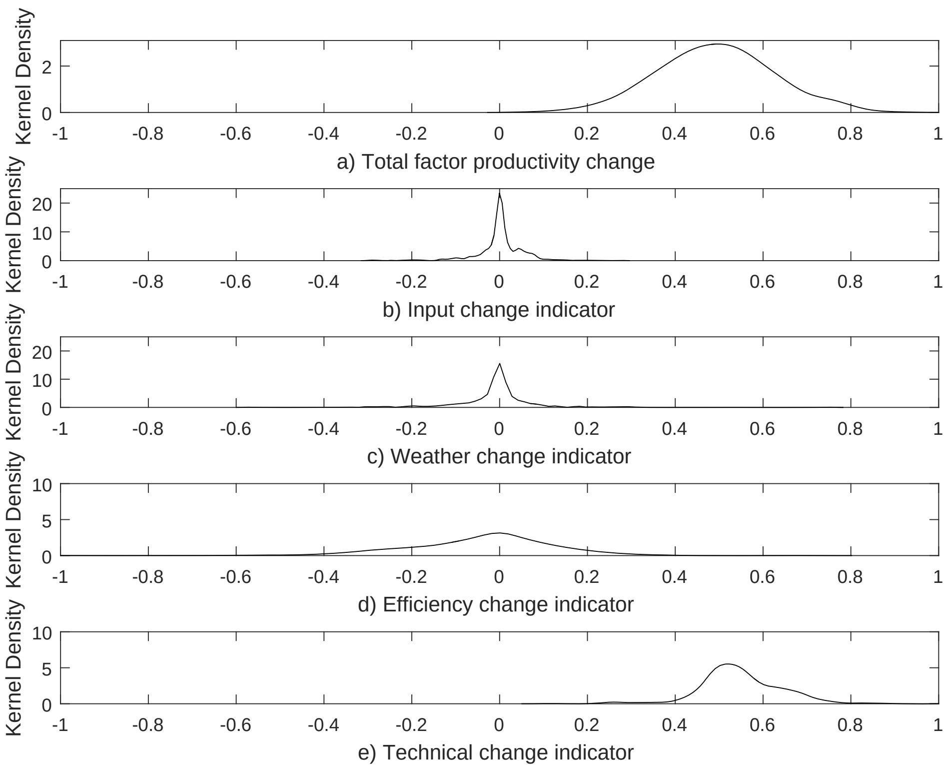


Figure 6: Decomposition changes in the United States between 1991-2004 and 1961-1974, kernel densities

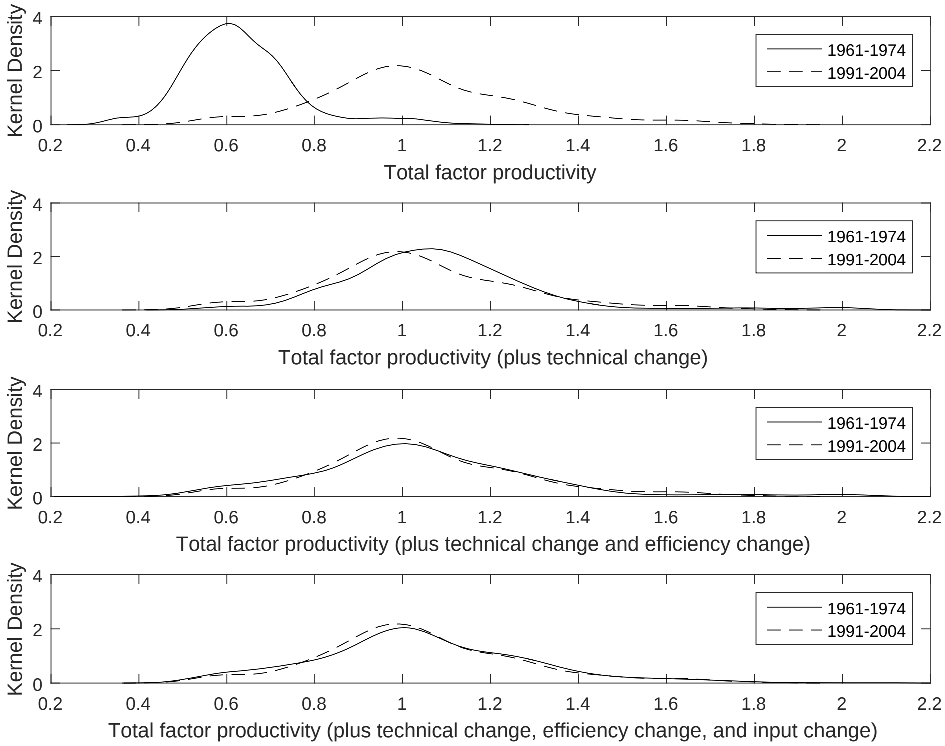


Figure 7: Counterfactual decomposition changes in the United States between 1991-2004 and 1961-1974, kernel densities

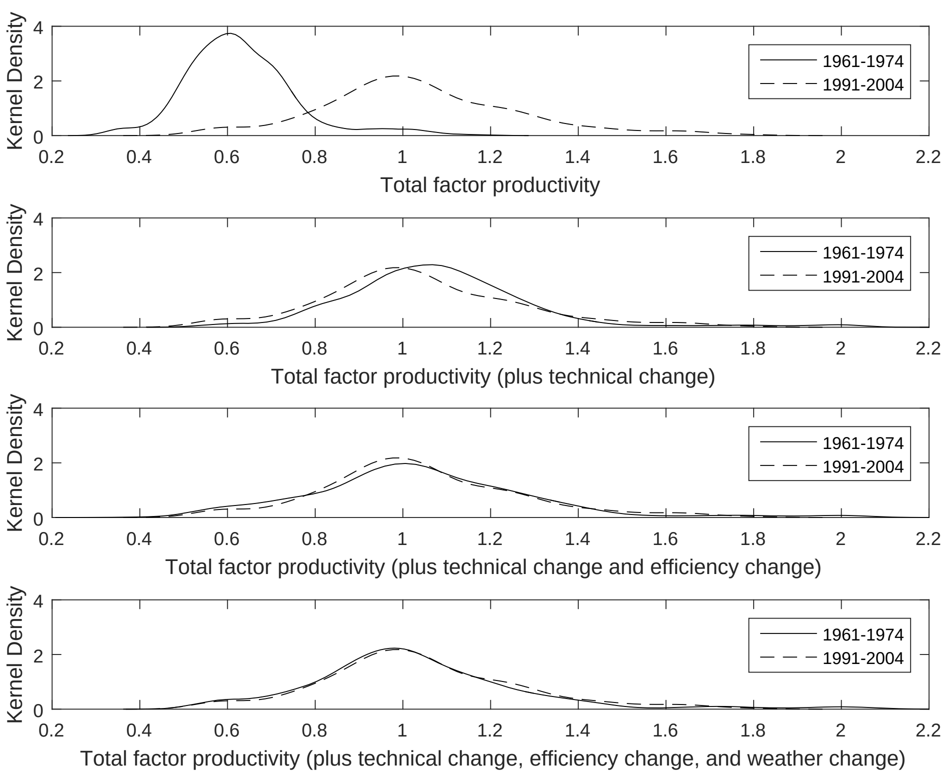


Figure 8: Counterfactual decomposition changes in the United States between 1991-2004 and 1961-1974, kernel densities

Table 1: Summary statistics of efficiency scores 1961-1974 and 1991-2004

	1961-1974		1991-2004			1961-1974		1991-2004	
	Mean	St. Dev.	Mean	St. Dev.		Mean	St. Dev.	Mean	St. Dev.
ALL US	0.7058	0.1663	0.6814	0.1725					
AL	0.7215	0.1325	0.6626	0.1037	NC	0.7972	0.0625	0.8508	0.0696
AR	0.7003	0.0592	0.7247	0.0435	ND	0.5607	0.0782	0.5855	0.0555
AZ	0.9392	0.0586	0.9612	0.0660	NE	0.7037	0.0599	0.7062	0.0574
CA	0.9990	0.0037	1.0000	0.0477	NH	0.5688	0.0456	0.5066	0.0409
CO	0.6468	0.0236	0.5786	0.0379	NJ	0.6896	0.0865	0.6842	0.0441
CT	0.6391	0.1147	0.6575	0.0574	NM	0.5237	0.0323	0.5272	0.0316
DE	0.9938	0.0114	0.8833	0.1013	NV	0.8603	0.0813	0.8985	0.1077
FL	0.9989	0.0041	0.9947	0.0155	NY	0.8056	0.0759	0.6463	0.0848
GA	0.7614	0.0616	0.8234	0.0575	OH	0.6618	0.0603	0.6484	0.0813
IA	0.9916	0.0245	0.9487	0.0552	OK	0.5526	0.0473	0.4387	0.0204
ID	0.7093	0.0295	0.7430	0.0365	OR	0.5533	0.0468	0.6200	0.0495
IL	0.9081	0.0577	0.8146	0.0760	PA	0.6582	0.0726	0.6148	0.0760
IN	0.7281	0.0722	0.7180	0.0764	RI	0.9908	0.0343	0.9423	0.1188
KS	0.6944	0.0575	0.6112	0.0485	SC	0.7031	0.1063	0.8122	0.1077
KY	0.6313	0.1146	0.5865	0.0475	SD	0.5976	0.0506	0.5757	0.0330
LA	0.7278	0.2064	0.7152	0.1040	TN	0.5690	0.0634	0.4836	0.0515
MA	0.6723	0.1067	0.6882	0.1092	TX	0.9712	0.0350	0.9101	0.0851
MD	0.6415	0.0424	0.6298	0.0368	UT	0.5816	0.0440	0.5225	0.0404
ME	0.6876	0.1110	0.6029	0.0689	VA	0.5814	0.0211	0.6012	0.0369
MI	0.5373	0.0267	0.6033	0.0433	VT	0.6693	0.0548	0.5795	0.0361
MN	0.7860	0.0851	0.8159	0.0477	WA	0.7035	0.0420	0.7380	0.0408
MO	0.6505	0.0699	0.5502	0.0470	WI	0.7975	0.0703	0.7365	0.0603
MS	0.6296	0.0787	0.6354	0.0923	WV	0.3999	0.1737	0.3508	0.0259
MT	0.5198	0.0321	0.4303	0.0379	WY	0.4624	0.0195	0.3499	0.0180

Table 2: Bias-corrected regression results correlating efficiency to weather

Period: 1961-2004	Coefficient		R^2
Temperature	-0.00015	***	0.01260
Moisture	0.04064	***	
Constant	-0.54670	***	
Period: 1961-1974	**Coefficient**		**R^2**
Temperature	-0.00043	***	0.01185
Moisture	0.07633	***	
Constant	-0.99701	***	
Period 1991-2004	**Coefficient**		**R^2**
Temperature	-0.00014	***	0.02540
Moisture	0.04182	***	
Constant	-0.41733	***	

$*\,*\,*$ indicates significance at 1% level. $**$ indicates significance at 5% level and $*$ indicates significance at 10% level.

Table 3: Decomposed changes for specific groups of US States

	Rank 1960	Rank 2004	TFP Δ	E Δ	T Δ	X Δ	W Δ	CVW Δ
				TOP TFP				
AL	5	8	0.4340	-0.0853	0.5143 ♦	-0.0029 ♦	-0.0017 ♦	21.5720
AZ	3	19	0.4284	0.0148	0.4033 ♦	-0.0194 ♦	-0.0028 ♦	13.5120
CA	2	1	0.4985	0.0089	0.6502	-0.1684	0.0156	6.0103
DE	6	5	0.4296	-0.1113	0.4824	0.1317	-0.0377 ♦	2.2540
FL	1	2	0.4784	0.0068	0.5432 ♦	-0.0559	-0.0033 ♦	28.6553
IA	4	3	0.4803	-0.0439	0.4918 ♦	0.0817	-0.0257 ♦	3.5024
IL	7	4	0.4992	-0.1110	0.5844	0.0463	-0.0206	6.2889
				BOTTOM TFP				
LA	44	37	0.5024	0.0105	0.5864 ♦	-0.1136	-0.0873 ♦	NA
MI	47	28	0.7140	0.1145	0.5814	0.0510	-0.0330	2.4960
MT	42	44	0.3470	-0.1906	0.5425	-0.0003	-0.0046	4.7860
NH	45	35	0.4288	-0.1159	0.6199 ♦	-0.0513	-0.0270	2.1980
OK	13	45	0.2949	-0.2285	0.5195	0.0019	0.0020	8.8600
WV	48	47	0.4843	-0.0838	0.5561 ♦	-0.0055	-0.0056	1.0590
WY	43	48	0.2363	-0.2790	0.5183	0.0012	0.0217	5.2720
TN	39	46	0.4184	-0.1625	0.5785	0.0086	-0.0174	5.6560
OR	46	15	0.6535	0.1143	0.5348	0.0027	0.0018	6.3620
				FASTEST TFP RATE of Δ 1960-2004				
IN	27	7	0.6123	-0.0151	0.6245	0.0395	-0.0362	3.5819
OR	46	15	0.6535	0.1143	0.5348	0.0027	0.0018	6.3620
MA	28	10	0.5608	0.0231	0.5483	-0.0425	0.0742	3.2400
MI	47	28	0.7140	0.1145	0.5814	0.0510	-0.0330	2.4960
				SLOWEST TFP RATE of Δ 1960-2004				
CO	9	32	0.4218	-0.1128	0.5409	-0.0001	0.0004	18.2950
KS	8	36	0.3887	-0.1275	0.5749	-0.0296	-0.0291	3.2410
OK	13	35	0.2949	-0.2285	0.5195	0.0019	0.0020	8.8600
TN	39	46	0.4184	-0.1625	0.5785	0.0086	-0.0174	5.6560
WY	43	48	0.2363	-0.2790	0.5183	0.0012	0.0217	5.2720
Average (48)			0.4965	-0.0438	0.5495	0.0018	-0.0131	7.2070

Table 4: Li tests on counterfactual 30-year decomposition changes between 1991-2004 and 1961-1974

	All 48 US States	
Null Hypothesis (H_0)	Statistic	p-value
$f(\frac{y_t}{x_t}) = h^T(\frac{y_0}{x_0} * exp(T\Delta_{t,0}))$	2.1836	0.0000
$f(\frac{y_t}{x_t}) = h^E(\frac{y_0}{x_0} * exp(T\Delta_{t,0}) * exp(E\Delta_{t,0}))$	-4.2246	0.2080
$f(\frac{y_t}{x_t}) = h^X(\frac{y_0}{x_0} * exp(T\Delta_{t,0}) * exp(E\Delta_{t,0}) * exp(X\Delta_{t,0}))$	-2.6611	0.3660
$f(\frac{y_t}{x_t}) = h^W(\frac{y_0}{x_0} * exp(T\Delta_{t,0}) * exp(E\Delta_{t,0}) * exp(W\Delta_{t,0}))$	-1.3766	0.5840

Note: The function f is a (kernel) function for the actual data in 1991-2004, while h^T, h^E, h^X, and h^W are (kernel) counterfactual distributions obtained by adjusting the 1961-1974 data for the effects of technological change (h^T), efficiency and technological changes (h^E), efficiency, technological and input changes (h^X), and efficiency, technological and weather changes (h^W), respectively.

Table 5: Infeasible cases by state in decomposition changes, 1991-2004 on 1961-1974

Climate and technological changes		
State	Number	Years
AZ	9	1992,1994,1996,1997,2000,2001,2002,2003,2004
FL	7	1991,1994,1995,1997,1998,2002,2003
IA	1	1993
LA	13	1991,1992,1993,1994,1995,1996,1997,1999,2000,2001,2002,2003,2004

Note: All cases of infeasibility are caused by the impossibility of computing the following element in the proposed decomposition: $f_0(x_t, w_t)$.