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Analysis of Technical Change, Efficiency Change, and Total Factor Productivity Change in U.S. Agriculture

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Abstract

This article examines factors driving technical change, technical efficiency change, and scale and mix efficiency change – all components of total factor productivity change – in U.S. agriculture. We use economic theory and previous literature to identify explanatory variables that could affect each component and examine some potentially important factors of total factor productivity change which have received less attention in the literature. Results show that technical change comes primarily from increased innovation through public research and improvements made in human capital. Technical efficiency change is driven by education, extension, the ratio of family-to-total labor, and some weather variables, while scale and mix efficiency change is significantly affected by farm size, all weather variables, and agro-temperature. Additionally, results show that some previously overlooked factors such as health care access play a crucial role in total factor productivity growth through its significant impact on technical change.

Keywords: scale and mix efficiency, technical change, technical efficiency, total factor productivity, U.S. agriculture

JEL Classification: D24, Q16

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Analysis of Technical Change, Efficiency Change, and Total Factor Productivity Change in U.S. Agriculture

Despite consistent growth in U.S. agricultural total factor productivity (TFP) over the last century, evidence of a recent slowdown in productivity growth has been observed (Fuglie 2008; Alston et al. 2010, p. 110; Ball, Schimmelpfennig and Wang 2013). For example, James et al. (2009) find a statistically significant slowdown in productivity growth after 1990 in their study focusing on agricultural productivity between 1949 and 2002. More alarming is the rate of slowdown – they further note that agricultural productivity growth has plummeted to half the rate that had been sustained for much of the 20th century.

Understanding sources of TFP growth and how it can be sustained is vital to ensure current and future food security, preserve the environment, mitigate the impact of climate change, and improve the U.S. agricultural industry's competitiveness internationally. Regarding the latter and despite the overall slowdown in agricultural productivity growth, Key and McBride (2007) conclude that live hog prices were nearly a third lower than they would have been without the productivity growth that occurred between 1992 and 2004. This decrease in price due to increased productivity help to give U.S. agriculture a competitive advantage in the export market where the U.S. is a net exporter of agricultural commodities.

The objective of this article is to examine factors driving total factor productivity change (TFPC) components for U.S. agriculture. We report the first analysis of how such factors as education, health care access, public and private research, extension, weather, and climate change affect technical change (TC), technical efficiency change (TEC), and scale and mix efficiency change (SMEC) for the entire U.S. agricultural industry in the 48 contiguous states.

These components of TFPC can be illustrated by reference to the concept of a production frontier. The production frontier identifies the maximum output that can be produced from given inputs and technology. A shift (which also results in a change in the maximum possible TFP) in the production frontier over time is referred to as technical change (Cummins and Xie 2013). Farrell (1957) defines technical efficiency as a ratio of actual production to production on the frontier. That is, any production not on the production frontier is technically inefficient production. Scale and mix efficiency measures the movement around the production frontier to capture economies of scale and movement from a production frontier where the input or output mix is restricted to another production frontier with no restrictions on input or output mix to capture economies of scope (O'Donnell 2012).

A major focus of previous research on TFP has been to examine the elasticity of TFP with respect to factors such as research and development (R&D) which provides vital information for understanding causal linkages. For example, R&D, education, and experience have been documented as major factors that affect agricultural TFP in the U.S. (e.g., Jorgenson and Griliches 1967; Ball et al. 1997; Ball et al. 1999; Alston, Craig and Pardey 1998; Huffman and Evenson 2006; Alston et al. 2011; Plastina and Fulginiti 2012). TFP change can be decomposed into technical change and efficiency measures (Farrell 1957; Capalbo 1988; Kuosmanen et al. 2009; O'Donnell 2012), and Jin et al. (2010) document that the magnitude of TFP is determined by changes both in efficiency and technical change. However, analysis of overall TFP provides little understanding of driving forces for these individual components of TFP.

Since TFP components ultimately determine TFP growth, decomposition of TFP provides a potentially fruitful avenue for more detailed understanding of the underlying sources of TFP growth, including some that have been largely ignored in the literature. Technical change is the main component pulling TFP upward (Ruttan 2002; O'Donnell 2012). Technical inefficiency leads to increased production costs and decreased TFP. Tian and Wan (2000) note that analyzing efficiency determinants is more important than presenting efficiency indices. That is, decomposition of TFP into its components is a first and necessary step but not sufficient. As Stewart, Veeman and Unterschultz (2009) note, decomposition of TFP into components permits evaluation of *how* TFP growth occurs, which is distinct from the causal assessments of *why* TFP growth happens. Whereas previous studies have examined *why* overall TFP growth occurs, this study differs by focusing on *why* growth of TFP components occurs.

Although some research has examined driving forces of technical change or efficiency measures for U.S. agriculture (e.g. Paul et al. 2004; Mayen, Balagtas and Alexander 2010; Key and Sneeringer 2014), none of these has explicitly calculated TFP first and then decomposed it into these components before examining the forces of change. An important weakness in calculating technical efficiency without decomposing TFP, for example, is the frequently imposed restrictive assumption of no technical change. Further, these studies have focused on particular sectors of the agricultural industry and to certain geographical regions. Consequently, they are unable to provide policy makers with comprehensive policy prescription for the entire agricultural industry. Our study differs first by addressing the prior weakness as we use technical change and efficiency measures decomposed from TFP change without additional restrictive assumptions. This is a three-stage approach where the first stage is calculation of TFPC, the second stage is decomposition of TFPC, and the third stage is examination of the decomposed TFPC components. Second, we examine the entire agricultural industry for the 48 contiguous states.

An important challenge, as Kuosmanen and Sipiläinen (2009) and O'Donnell (2012) highlight, has been a lack of coherent information on TFP change components. In addition, they note that prior decompositions calculated using the axiomatic approach have been inexact due to mixing of prices and quantities from different periods and failing to satisfy economically sound and relevant axioms from index number theory, i.e. the identity and transitivity axioms. [1] O'Donnell (2012) addresses these concerns in his calculation of U.S. agricultural TFP indices and decomposition into TC, TEC, and SMEC.

The contributions of this research are twofold. First, we use the components of TFPC (TC, TEC and SMEC) recently calculated by O'Donnell (2012) and examine factors affecting them using a state-level panel data series for the contiguous 48 states. Second, we examine overall TFPC utilizing a broader range of potential drivers, including health care access and agro-climatic conditions, which have not been previously examined.

Results indicate that education, health care access, both private and public research and their spill-ins are the main factors affecting TC. TEC is affected by education, extension, the ratio of family-to-total labor, and some of the weather variables. SMEC is significantly affected by farm size, all weather variables, and agro-temperature. Additionally, results show that some previously overlooked factors such as health care access play a crucial role in TFPC through its significant impact on technical change.

The article proceeds as follows. We first briefly present the theory of total factor productivity, its decomposition, and the empirical models along with justification for our choice of regressors for each component. We discuss the panel data and method of estimation in the following section. Empirical results from diagnostic tests and the TC, TEC, SMEC, and TFPC models are presented in the subsequent section. The final section concludes.

[1] The axiomatic approach postulates a number of properties that any meaningful index number should satisfy, and then tries to construct an ideal index number formula to meet the axioms. These indices assume very little about the economic objectives of the firms or their production technology. All that is required is price and quantity data of inputs and outputs, e.g. Fisher and Törnqvist indexes (Kuosmanen and Sipiläinen 2009).

Theory and Empirical Models

TFP can be defined as the ratio of the total output level to total factor (or input) level. O'Donnell (2008) shows that TFP for state *i* in period *t* can be expressed mathematically as: $TFP_{it} = Y_{it}/X_{it}$, where $Y_{it} \equiv Y(\boldsymbol{y}_{it})$ is aggregate output, $\boldsymbol{y}_{it} \in i_{+}^{M}$ is a vector of output quantities, $X_{it} \equiv X(\boldsymbol{x}_{it})$ is aggregate input, and $\boldsymbol{x}_{it} \in i_{+}^{N}$ is a vector of input quantities. Output quantities are measures of quantities sold plus on-farm consumption and net changes in inventories, and input quantities are measures of purchased inputs and those inputs provided on the farm (O'Donnell 2012). The functions $Y(\cdot)$ and $X(\cdot)$ are aggregators required to be nonnegative, nondecreasing, and linearly homogeneous. Productivity change for state *i* from time $t-1$ to t is:

$$(1) \qquad \frac{TFP_{it}}{TFP_{it-1}} = \left(\frac{Y_{it}}{X_{it}}\right) / \left(\frac{Y_{it-1}}{X_{it-1}}\right) = \left(\frac{Y_{it,it-1}}{X_{it,it-1}}\right),$$

where $Y_{it,it-1} \equiv \left(\frac{Y_{it}}{Y_{it-1}}\right)$ is an output index (measuring the change in aggregate output level between periods *t* – 1 and *t*) and $X_{it,t-1} \equiv \left(\frac{X_{it}}{X_{it-1}}\right)$ is an input index (measuring the change in aggregate input level between periods *t* – 1 and *t*). In order for the TFP indexes to satisfy the basic index axioms, appropriate vectors of reference output and input prices, $\boldsymbol{p}_0$ and $\boldsymbol{w}_0$, must be used as weights.[2] Thus, equation (1) can be re-written as

$$(2) \qquad \frac{TFP_{it}}{TFP_{it-1}} = \left(\frac{\boldsymbol{p}_0\boldsymbol{y}_{it}}{\boldsymbol{p}_0\boldsymbol{y}_{it-1}}\right) \times \left(\frac{\boldsymbol{w}_0\boldsymbol{x}_{it-1}}{\boldsymbol{w}_0\boldsymbol{x}_{it}}\right).$$

O'Donnell (2008, 2012) shows that TFPC can be decomposed into TC, TEC and SMEC as:

$$(3) \qquad \frac{TFP_{it}}{TFP_{it-1}} = \left(\frac{TFP_{it}^{*}}{TFP_{it-1}^{*}}\right) \times \left(\frac{OTE_{it}}{OTE_{it-1}}\right) \times \left(\frac{OSME_{it}}{OSME_{it-1}}\right),$$

where $TFP_{it}^{*} \equiv \left(\frac{Y_{it}^{*}}{X_{it}^{*}}\right)$ and $TFP_{it-1}^{*} \equiv \left(\frac{Y_{it-1}^{*}}{X_{it-1}^{*}}\right)$ represent maximum possible TFP for state *i* in period *t* and *t* – 1, respectively, using the available technology in each period (measure of technical change);

[2] O'Donnell (2012) notes that $\boldsymbol{p}_0$ and $\boldsymbol{w}_0$ can be any price vector representative of the price vector faced by all firms in the dataset. He uses sample means of prices in all states (*I*) in all periods (*T*), i.e. $\boldsymbol{p}_0 = \bar{\boldsymbol{p}} = (IT)^{-1}\sum_i\sum_t \boldsymbol{p}_{it}$ and $\boldsymbol{w}_0 = \bar{\boldsymbol{w}} = (IT)^{-1}\sum_i\sum_t \boldsymbol{w}_{it}$.

Y_{it}^* and X_{it}^* are output and input levels at the maximum TFP point; $OTE_{it} \equiv Y_{it}/\bar{Y}_{it}$ (a measure of technical efficiency), and $\bar{Y}_{it}$ is the maximum aggregate output level possible for a fixed observed input level and output mix; $OSME_{it} = OME_{it} \times ROSE_{it}$(a measure of scale and mix efficiency), OME_{it} is output-oriented mix efficiency defined as $OME_{it} \equiv \bar{Y}_{it}/\hat{Y}_{it}$(measure of potential gains that can be achieved through economies of scope), $\hat{Y}_{it}$ is the maximum output level that can be produced with no restriction on output mix using X_{it} units of inputs; $ROSE_{it}$ is residual output-oriented scale efficiency defined as $ROSE_{it} \equiv \left(\frac{\hat{Y}_{it}}{X_{it}}\right) / \left(\frac{Y_{it}^*}{X_{it}^*}\right)$, a movement around an unrestricted production frontier, i.e., a movement from one mix-efficient point to another (scale effect), and the term residual refers to potential residual mix effect in this scale effect. Thus, equation (3) can be rewritten in terms of Y_{it} and X_{it} as:

(4) $$\frac{TFP_{it}}{TFP_{it-1}} = \left(\frac{Y_{it}^*/X_{it}^*}{Y_{it-1}^*/X_{it-1}^*}\right) \times \left(\frac{Y_{it}/\bar{Y}_{it}}{Y_{it-1}/\bar{Y}_{it-1}}\right) \times \left(\frac{\bar{Y}_{it}/\hat{Y}_{it}}{\bar{Y}_{it-1}/\hat{Y}_{it-1}}\right) \times \left(\frac{[\hat{Y}_{it}/X_{it}]/[Y_{it}^*/X_{it}^*]}{[\hat{Y}_{it-1}/X_{it-1}]/[Y_{it-1}^*/X_{it-1}^*]}\right),$$

which simplifies to equation (1).

From equation (3) the relationship between TFPC and its components is multiplicative and can be represented as:

(5) $$TFPC_{it} = TC_{it} \times TEC_{it} \times SMEC_{it},$$

where TC_{it} is technical change, and TEC_{it} and $SMEC_{it}$ are output-oriented technical efficiency change and scale and mix efficiency change measures, respectively.[3]

We analyze how each of these components is affected by various factors that potentially affect TFPC. Letting $TFPC_{it} = f(Z) + \varepsilon_{it}$, where $Z = \{R_{it}, W_{it}, S_{it}\}$ represent the regressors, R are

[3] O'Donnell (2012) calculates output-oriented efficiency measures. Efficiency components can be split into sub-components for inputs (input-oriented) and outputs (output-oriented), offering a detailed picture of the constituents of productivity change (Kuosmanen and Sipiläinen, 2009). Chen and Huffman (2003) note that output-oriented and input-oriented measures of technical efficiency agree if and only if the technology exhibits constant returns to scale. The output-oriented measures are more common in empirical work.

research variables, W are weather variables, S are other variables that affect overall TFPC, we identify factors expected to affect each of the components. That is, we select a subset of regressors, $g(z)$, from set Z for each component. So $C = \{g(z) \in Z\} + \varepsilon_{it}$, where C is the component, TC_{it}, TEC_{it} or $SMEC_{it}$, and ε_{it} is the random disturbance term with expected mean of zero for each equation. We present the TFPC component models below and justify the choice of our regressors after presenting each model. One of the important challenges is the *ex-ante* difficulty of identifying potential factors affecting the components. We rely on economic theory, previous literature, and logic to identify factors that potentially drive each of the components. We allow for the possibility that some regressors are drivers for more than one component.[4]

Technical Change

$$(6) \quad lnTC_{it} = \alpha_1 + \alpha_2 lnEd_{it} + \alpha_3 lnHs_{it} + \alpha_4 lnRpub_{it} + \alpha_5 lnRpubS_{it} + \alpha_6 lnRpri_{it} + \alpha_7 lnRpriS_{it} + \alpha_8 (lnRpri_{it}) D_{96} + \alpha_9 (lnRpriS_{it}) D_{96} + \sum_{r=1}^{6} \beta_r D_r + \varepsilon_{it},$$

where *TC* is the technical change component of TFPC, *Ed* is farmers' education level, *Hs* is rural health care access, *Rpub* is the stock of public agricultural research investments, *RpubS* is public agricultural research spill-in, *Rpri* is the stock of private agricultural research investments, *RpriS* is private agricultural research spill-in, D_{96} is a dummy variable for method of data calculation for *Rpri* that changed after 1996 (the period 1997 to 2003 gets the value of 1), D_r are regional dummy

[4] O'Donnell (2014) notes that TFPC can be further decomposed to include an environmental efficiency measure. With no environmental efficiency component, we include environmental variables in the TEC estimation equation and both environmental and agro-climatic variables in the SMEC equation. Our logic for this selection is provided after presenting each of the models. Education and health care access are the other regressors in more than one component model. Both are included in the TC and TEC models.

variables that are included based on the results of the Hausman test for regional fixed effects (reported later), α and β are parameters to be estimated.

TC is the shift in the production frontier over time which also results in a change in the maximum possible TFP. Ruttan (2002), Stewart, Veeman and Unterschultz (2009), O'Donnell (2010), and Jin et al. (2010) all note that investments in research and technology help develop innovations that potentially result in TC. R&D brings advances in physical technologies as well as more knowledge which in turn can lead to improvement in planning and decision making. For example, Fuglie and Heisey (2007) found that every $1 invested in public agricultural research expenditures in the U.S. generated $10 in return. Examining agricultural production in China, Jin at al. (2010) identified technology, research, and the introduction of new crop varieties as factors behind TC-based TFP in the crop and livestock sectors. Mullen (2007) found that public and private investments in research significantly contributed to TC that improved agricultural productivity in Australia. We account for the impacts of both public and private research on technical change in U.S. agriculture.

Huffman and Evenson (2006) document that public funds invested in one state have direct benefits in that state and also can indirectly benefit other states within the same geo-climatic region as the state making the investment. That is, there is a spill-in effect from research conducted in contiguous states which contributes to each state's productivity. Pardey and Alston (2011) estimate that roughly one-third of the benefits of state-level agricultural R&D are generated through spill-in of research conducted in other states. Thus, R&D in one state is nonexcludable and potentially contributes to TC not only within the state the research is conducted but in nearby states.

As farmers are typically the end users of agricultural R&D innovations, their human capital is potentially a contributing factor to TC. Human capital of the labor force is a measure of its quality and includes skill level and health status (Fuglie and Rada 2013). Skill is enhanced through education. McCunn and Huffman (2000) and Reimers and Klasen (2013) note that farmers' education has been shown to affect farmers' decisions to adopt and make maximum use of new inventions. That is, farmers' level of education potentially contributes to TC by enabling the farmer to adopt and use these innovations from private and public research. The labor data used by O'Donnell (2012) to identify the components of TFPC (TC, TEC and SMEC), our dependent variables, were adjusted for quality changes. The quality changes included those based on educational differences. Consequently, if a significant effect of education level on TC is found in this study, it can be interpreted as a residual effect beyond that incorporated into the labor series as quality adjustments.

Additionally, a healthier work force can contribute to TC not only through greater physical productivity but also by being better able to assimilate new production practices and innovations. Further, a healthy farmer is more willing and may have more resources to invest in new technologies than an unhealthy farmer who may be limited due to spending resources and time on resolving a poor health condition. Thus, in addition to a farmer's education level, her health status potentially affects TC. For instance, looking at the health status of Norwegian farmers and its impact on productivity, Loureiro (2009) finds that including health status is necessary to properly model productivity gains from capital and technological improvements. Lacking data on health status of agricultural labor, we use a measure of health care access as a proxy variable.

Technical Efficiency Change

$$(7) \qquad lnTEC_{it} = \alpha_1 + \alpha_2 lnEd_{it} + \alpha_3 lnHs_{it} + \alpha_4 lnExt_{it} + \alpha_5 lnFs_{it} + \alpha_6 lnFtlratio_{it} + \alpha_7 lnPrecp_{it} + \alpha_8 lnGDD_{it} + \alpha_9 lnDDD_{it} + \alpha_{10}(lnGDD_{it})D_s + \alpha_{11}(lnGDD_{it})D_n + \alpha_{12}(lnDDD_{it})D_s + \alpha_{13}(lnDDD_{it})D_n + \varepsilon_{it},$$

where *TEC* is the technical efficiency change component of TFPC, *Fs* is farm size, *Ext* is the stock of public extension investments, *Ftlratio* is the ratio of family labor to total labor, *Precp* is annual total rainfall, *GDD* is growing degree days, *DDD* is damaging degree days, D_s, and D_n are indicator variables for Southern and Northern states, respectively.

While adoption of new production practices has the potential to impact TC, the farmer's ability to use and improve the method of applying the available technology has potential to increase technical efficiency. Tian and Wan (2000) state that technical inefficiencies are likely to be affected by a wide variety of factors which include biological and human capital. The latter can be increased through formal education and training and improved health. They can be complemented by external services and socioeconomic conditions influenced by public policy. O'Donnell (2010) notes that complementary policies designed to increase technical efficiency include education, training, and extension programs. As with TC, a significant effect of education level on TEC would be interpreted as a residual effect beyond that accounted for in the adjustments for labor quality.

Farmers receiving more extension services are expected to develop better management skills, i.e., the ability to do the right things at the right time in the right way in order to better utilize existing technologies to increase their technical efficiency. Mullen (2007) notes that extension plays a critical role by giving farmers reliable information on new technologies and understanding how these technologies can be used to their fullest. Useful information, theoretical or practical, has the potential to help farmers move from inefficient production toward production on the frontier. This is further documented by Jin et al. (2010) who conclude that deterioration of the extension system almost certainly will have a negative effect on TFPC mainly through affecting the efficiency of farming by not teaching farmers how to use newly available technologies.

Average farm size in the U.S. has increased dramatically and consistently over the past century. Cummins and Xie (2013) note that expansion of firms has potential to create inefficiencies primarily due to management inefficiency and decreasing productivity of variable inputs. On the other hand, Paul et al. (2004) find that small family farms are generally less efficient in terms of both their scale of operations and technical aspects of production than are large farms. Thus, farm size is a potentially important factor for TEC. Although not an unambiguous theoretical hypothesis, larger farms (over the range of state-level average farm sizes) are expected to be more efficient than smaller farms and so have a positive effect on TEC.

How much time the farmer spends on the farm or how heavily the farmer relies on hired labor potentially affects her managerial ability. Yee, Ahearn and Huffman (2004) note that the majority of workers on U.S. farms are the operators and their families. They contribute at least two thirds of the hours worked. The ratio of family-to-total labor is included as a measure of farmers' self-sufficiency. The expected impact of this variable is ambiguous. It can either positively or negatively affect TEC. For example, having more hired labor may enable the family labor to focus more on management activities thereby positively impacting TEC. Alternatively, the hired labor may be more experienced than some of the family labor, in which case relying on family labor can be detrimental to TEC. On the other hand, hired labor may have different objectives than family labor which could create a moral hazard problem, in which case having more hired labor relative to family labor may negatively affect TEC.

Technical inefficiency in agricultural production can also be attributed to undesirable events beyond the farmer's control such as poor weather. Although changes in management practices can counter the effects of a changing environment on TEC, unexpected weather conditions potentially affect TEC in the short run. For example, Key and Sneeringer (2014) find a negative relationship between expected heat stress and the technical efficiency of dairies across the U.S. We include three variables in our TEC equation. Rainfall is included as total annual precipitation. Two temperature variables are included to capture a twofold effect. First, crops have a range of temperatures that enhance their growth. Second, there are extreme temperatures that negatively affect growth. For instance, optimal growing temperature for corn is 8 - 29°C and any temperature above 29°C has a damaging effect on growth (Roberts, Schlenker and Eyer 2012). We capture these two effects of temperature through growing degree days and damaging degree days (explained in the data section). We also acknowledge the existence of heterogeneous weather conditions effects on TEC between the Northern, Central and Southern bands of states and we include growing degree day and damaging degree day interaction terms to identify this difference. However, we do not include any interaction terms for precipitation because of prior evidence of little difference in their effect across regions (McCarl et al. 2008).

Scale and Mix Efficiency Change

(8)
$$lnSMEC_{it} = \alpha_1 + \alpha_2 lnFs_{it} + \alpha_3 lnTT_{it} + \alpha_4 lnPrecp_{it} + \alpha_5 lnGDD_{it} + \alpha_6 lnDDD_{it} + \alpha_7 lnAgrotemp_{it} + \alpha_8 lnAgroprecp_{it} + \alpha_9 (lnGDD_{it})D_s + \alpha_{10}(lnGDD_{it})D_n + \alpha_{11}(lnDDD_{it})D_s + \alpha_{12}(lnDDD_{it})D_n + \alpha_{13}(lnAgrotemp_{it})D_s + \alpha_{14}(lnAgrotemp_{it})D_n + \alpha_{15}(lnAgroprecp_{it})D_s + \alpha_{16}(lnAgroprecp_{it})D_n + \alpha_{17}D_{83} + \sum_{r=1}^{6}\beta_r D_r + \varepsilon_{it},$$

where *SMEC* is the scale and mix efficiency change component of TFPC, *TT* is the ratio of aggregate output price to aggregate input price, *Agrotemp* is the 50-year rolling average for temperature, *Agroprecp* is the 50-year rolling average for rainfall, and D_{83} is an indicator variable for the 1983 Payment In Kind (PIK) program.

Economic and related incentives largely bring about the movement from one technically efficient point to another through changing total input and output levels or their combinations. O'Donnell (2012) argues that subsidies and tax policies have an impact on SMEC. Policies mainly alter incentives and change expectations. For example, the 1983 Payment-In-Kind (PIK) program through which the Federal Government encouraged farmers to reduce crop production in order to lower accumulated government-held commodity surpluses potentially affected SMEC in different ways than did policies that were in place for longer periods.

As Coelli et al. (2005, p. 4) point out, a firm may be technically efficient but may still be able to improve its productivity by exploiting scale economies through increasing output or by exploiting economies of scope through changes in the output or input mix. Farm size potentially impacts a farm's SMEC through both scale and scope. Previous research found that large farms are more scale efficient than small farms. For example, Paul et al. (2004) examined the trend toward consolidation in U.S. agriculture and found significant scale and efficiency advantages for large farms. Input and output combinations often change as farm size changes. Unless production is homothetic, profit-maximizing input ratios and output ratios are both functions of output level which in turn is affected by farm size.

O'Donnell (2010) notes that improvements in terms of trade (our variable *TT* which is the ratio of aggregate output to input prices) encourage technically efficient optimizing firms to expand their operations (further) into the region of decreasing returns to scale (and scope), with the result that increases in profitability can be associated with falls in productivity. Thus, terms of trade potentially have an impact on farmers' decisions of scale, mix of inputs, and mix of outputs. Yet, the speed of adjustment may be quite slow. A major limitation in changing scale or mix of inputs or outputs is what Chhetri et al. (2010) refer to as the inertia of sunk costs. Farmers willing to add new inventions that could alter their scale or input or output mix may have limited resources to do so because of high investment in prior technology.

Agricultural production is a biological process heavily affected by weather and agro-climatic conditions. Weather (precipitation and temperature in our case) can be a deterrent or motivation for farmers to use more inputs in production that could affect SMEC. Consequently, as in the TEC equation, we include precipitation, growing degree days, and damaging degree days, as well as regional dummy interaction terms for the two temperature variables in this equation.

Additionally, agro-climatic conditions also play an important role in determining the magnitude of production and can also play an *ex ante* role in affecting input and output combinations and thus SMEC. Deschênes and Greenstone (2007) highlight that, in response to a change in climate, farmers may alter their use of fertilizers, change their mix of crops, or even decide to use their farmland for another activity. The impact of the agro-climatic conditions likely differ between the Southern, Central, and Northern bands of states. We include interaction terms to determine this difference.

Total Factor Productivity Change

For comparison with the component models and with previous literature, we estimate the TFP model including all explanatory variables hypothesized to affect individual components.

(9) $lnTFPC_{it} = \alpha_0 + \sum_{k=1}^{25} \alpha_k ln\, G_{it} + \alpha_{26} D_{83} + \sum_{r=1}^{6} \beta_r\, D_r + \varepsilon_{it},$

where G_{it} are all the variables and interaction terms in the component models.

Data and Empirical Approach

We use a balanced panel annual data set with 2,064 observations that covers the 48 contiguous states for the period 1961 to 2003. TFPC, TC, TEC and SMEC were calculated by O'Donnell (2012) using an annual state-level panel dataset of prices and quantities for three outputs (crops, livestock and other outputs) and four inputs (land, labor, capital and materials) compiled by the USDA/ERS for the years 1960-2004 (USDA 2013).[5] We make use of the same dataset for some of our variables (described below) but drop years 1960 and 2004 due to the lack of observations in those years for some of our other regressors.

TFP was calculated by O'Donnell (2012) as a ratio of output to input values with outputs and inputs aggregated using the functions $\boldsymbol{Y}(\boldsymbol{y}_{it}) \propto \boldsymbol{p}_0' \boldsymbol{y}_{it}$ and $\boldsymbol{X}(\boldsymbol{x}_{it}) \propto \boldsymbol{w}_0' \boldsymbol{x}_{it}$. TC, TEC and SMEC were estimated using data envelope analysis (DEA) methodology. TC was estimated by solving $TFP_t^* = \max_{\boldsymbol{\theta},\omega,\boldsymbol{v}}\{\boldsymbol{p}_0'\boldsymbol{\omega}: \boldsymbol{\omega} \leq \boldsymbol{Y\theta}; \boldsymbol{X\theta} \leq \boldsymbol{v};\ \boldsymbol{w}_0'\boldsymbol{v} = 1;\ \boldsymbol{\theta}'\boldsymbol{\iota} = 1;\ \boldsymbol{\theta}, \boldsymbol{\omega}, \boldsymbol{v} \geq 0\}$ where $\boldsymbol{\omega} \leq \boldsymbol{Y\theta}$ and $\boldsymbol{X\theta} \leq \boldsymbol{v}$ are the constraints to the production possibilities set, $\boldsymbol{\theta}$ is a $J_t \times 1$ vector, $\boldsymbol{\iota}$ is a $J_t \times 1$ unit vector, and J_t is the number of observations used to estimate the frontier in period t. TEC was estimated by solving $Y_{it}/\bar{Y}_{it}$=$\min_{\lambda,\boldsymbol{\theta}}\{\lambda^{-1}: \lambda\boldsymbol{y}_{it} \leq \boldsymbol{Y\theta}; \boldsymbol{X\theta} \leq \boldsymbol{x}_{it}; \boldsymbol{\theta}'\boldsymbol{\iota} = 1; \lambda, \boldsymbol{\theta} \geq 0\}$ where $\lambda^{-1} = \boldsymbol{Y}(\boldsymbol{y}_{it})/\boldsymbol{Y}(\lambda\boldsymbol{y}_{it})$. Scale efficiency change was computed by taking the ratio of $[\min_{\lambda,\boldsymbol{\theta}}\{\lambda^{-1}: \lambda\boldsymbol{y}_{it} \leq$

[5] The term change (C) in TFPC, TEC, and SMEC refers to changes in TFP, technical efficiency, and scale and mix efficiency in comparison to California in 1960 which had TFP = 1, was fully technically efficient and scale and mix efficient. For TC, the comparison was to the Pacific region (one of the ten USDA ERS farm production regions) which had TC = 1 in 1960).

$\boldsymbol{Y\theta}; \boldsymbol{X\theta} \leq \boldsymbol{x}_{it}; \lambda, \boldsymbol{\theta} \geq 0\}]/[\min_{\lambda,\boldsymbol{\theta}}\{\lambda^{-1}: \lambda \boldsymbol{y}_{it} \leq \boldsymbol{Y\theta}; \boldsymbol{X\theta} \leq \boldsymbol{x}_{it}; \boldsymbol{\theta}'\boldsymbol{\iota} = 1; \lambda, \boldsymbol{\theta} \geq 0\}]$ where the numerator is an estimate of TEC under constant returns to scale, the denominator is an estimate of TEC under variable returns to scale. Mix efficiency change was computed by solving $Y_{it}/\hat{Y}_{it} = \min_{\boldsymbol{\theta},z}\{\boldsymbol{p}_0'\boldsymbol{y}_{it}/\boldsymbol{p}_0'\boldsymbol{\omega}: \boldsymbol{\omega} \leq \boldsymbol{Y\theta}; \boldsymbol{X\theta} \leq \boldsymbol{x}_{it};\ \boldsymbol{\theta}'\boldsymbol{\iota} = 1;\ \boldsymbol{\theta}, \boldsymbol{\omega} \geq 0\}$.

Liu et al. (2009) developed data for health care access and farmers' education level by state for 1961 to 1999. We updated them to 2003 using the same procedures. Health care access was proxied by Medical Doctors (MDs) per 10,000 population in rural counties of each state. County-level data on the number of MDs and population in each state were from the Bureau of Health Professions National Center for Health Workforce Analysis (2012). For identification of rural counties, the Urban Influence Code (UIC) developed by USDA/ERS (2003) which divides counties into metropolitan counties and nonmetropolitan (rural) counties was used. State-level data for MDs per 10,000 population was then calculated as a simple average of total MDs in all rural counties in each state per 10,000 population.

Farmers' education level was approximated by an index of weighted average weekly working hours across various education levels and types of employment for each state. The index was constructed by Liu et al. (2009) using data from Ball (2005), and we updated it using data from Ball (2013).

Public agricultural research and public agricultural extension stock data were from Huffman (2012). The stock of public agricultural research was calculated using state-level expenditure data for agricultural research on agricultural productivity. These data came from the USDA's Current Research Information System (CRIS). The stock variable was the sum of expenditures based on a 35-year trapezoidal knowledge decay function (Wang et al. 2013). The stock of public agricultural extension (Huffman 2012) was calculated as a stock of full-time-equivalent professional extension staff. The stock was calculated based on a 5-year exponentially declining weight. The private research stock data was measured from the inventory of patents for agriculture as the source of use industry (Johnson 2013) and considering a 19-year trapezoidal decay function (Wang et al. 2013).

We measured spill-in for both public and private research using spatial weights derived by Huffman (2009). The spatial weights were calculated as a share of all agricultural production for each state in the geo-climatic region relative to the sum of all agricultural production for all states in the region. Public research spill-in for state *i* was then calculated as the sum of the weighted public agriculture research capital for all other states, except state *i,* in the same geo-climatic region. This method is similar to that used by Liu et al. (2009) but uses Huffman's (2009) 16 geo-climatic regions rather than the 10 ERS regions. Huffman found that spill-in variables based on the geo-climatic regions performed significantly better (based on t-values and R^2) than the variables based on the ERS regions.

Average farm size for each state was measured as the real gross value of farm assets per farm. Yee and Ahearn (2005) argue that this measure is preferred to acreage since it accounts for the productive capacity of land. We use the Farm Balance Sheet data from USDA/ERS (1961-2003) and deflate the gross value of farm assets to 2003 dollars using the Bureau of Economic Analysis' chain-type GDP deflator from the St. Louis Federal Reserve Bank's Alfred service (series B191RG3A086NBEA). This is the same deflator used by the ERS.

We used the USDA (2013) state-level data to calculate the ratio of family-to-total labor. Using the same data set, terms of trade was measured as a ratio of aggregate output price to aggregate input price following O'Donnell (2008).

Precipitation, in centimeters, was measured as the accumulated total per calendar year. Monthly averages for each state were from the National Climatic Data Center/National Oceanic and Atmospheric Administration (NCDC/NOAA).

Temperature was proxied by growing degree days and damaging degree days. These are measures of crops' accumulated exposure to optimal growing temperature or extreme temperature, respectively, during the growing season. The county-level data for both growing degree days and damaging degree days for the months April to November (the period which encompasses the growing season for most crops) each year were from Roberts (2013). Deschênes and Greenstone (2007) document that the effect of heat accumulation is nonlinear since temperature must be above a threshold for plants to absorb heat and below a ceiling since plants cannot absorb extra heat when temperature is too high. While the upper bound and lower bound vary by crop, previous literature (e.g., Schlenker, Hanemann and Fisher 2006; Deschênes and Greenstone 2007; Roberts, Schlenker and Eyer 2012) generally follows Ritchie and NeSmith (1991, pp. 5-29) who suggested characterizing the entire agricultural sector using a base of 8°C and a ceiling of 32°C. Growing degree days were measured by summing $min\left\{\frac{T_h+T_l}{2}, T_m\right\} - T_b$ across days between April 1 and November 30, where T_h is the day's maximum temperature, T_l is the day's minimum temperature, T_m is the upper bound growing temperature (32°C), and T_b is the lower bound growing temperature (8°C). Damaging degree days were calculated using the sum across days of $\left\{\frac{T_h+T_l}{2} - T_m\right\}$ when $\frac{T_h+T_l}{2} > T_m$. State-level data were computed as the simple average for all counties in each state.

Fifty-year rolling averages (starting from 1911) for precipitation and temperature were used as proxies for agro-climatic conditions (agro-precipitation and agro-temperature). Agro-temperature was calculated as the 50-year average temperature during the growing season from April to November, and agro-precipitation was calculated as the 50-year average total annual rainfall. Monthly averages for each state were from the National Climatic Data Center/National Oceanic and Atmospheric Administration (NCDC/NOAA).

We present summary data statistics in Table 1. They show that states vary greatly in terms of farm size, extension professional staff, public and private research investment, private research spill-in, and damaging degree days. Health care access also varies considerably across states but not as much as the above variables.

Figure 1 shows the relationship between TFPC and its components between 1961 and 2003. TFPC and TC have an upward trend, TEC is relatively flat and smooth, and SMEC fluctuates throughout the period of study. Most of the growth in TFPC is due to technical change.

Results

Our dataset is likely to be subject to heteroskedasticity, contemporaneous correlation across panels, and auto-correlation within panels. We test for heteroskedasticity and autocorrelation for each model using the Modified Wald test and Wooldridge test, respectively. Results show that we cannot reject the presence of heteroskedasticity or autocorrelation in our dataset for any of the four models. In addition, we perform the Hausman specification test (Hausman 1978), to determine whether to use a random or fixed effects panel data estimator. Hausman test results support using a fixed-effects estimator for three of our models (TC, SMEC and TFPC) and a random-effects estimator for the TEC model. Results for these diagnostic tests are presented in Table 2. Following Huffman and Evenson (2006) and Huffman (2009), we use regional (rather than state) fixed effects, in the three models using the fixed-effects estimator, for seven geographic regions (Northeast, Southeast, Central, Northern Plains, Southern Plains, Mountain, Pacific). These regions are based on the 10 ERS regions with the New England region combined with the Northeast region, the Appalachian region combined with the Southeast region, and the Lake States region combined with the Corn Belt region. The Corn Belt region is treated as the baseline for comparison with the other regions, so no dummy variable is included for this region.

We estimate all three component and TFPC models using the Prais-Winsten panel corrected standard errors (PCSE) estimator with AR1 autocorrelation. As Beck and Katz (1995) document, this approach works well with panel data when correcting for heteroskedasticity, contemporaneous correlation across panels, and autocorrelation within panels.

Results from the TFPC component models are reported in Table 3. The estimates are reported in the three columns, technical change (TC), technical efficiency change (TEC) and scale and mix efficiency change (SMEC), respectively.

Coefficient estimates of explanatory variables in the TC model are all significant at the 0.05 level except for education which is significant at the 0.10 level. These results show that education, health care access, public research, public research spill-in, and private research all have a positive effect on TC while private research spill-in has a negative effect on TC. Except for the Southern Plains region, results show a statistically significant and positive difference between each of the other regions and the Corn Belt region. These results show that public research conducted in other states within the same geo-climate region (public research spill-in) has the largest effect on the state's TC. A 1 percent increase in public research spill-in results in a 0.42 percent increase in TC. The next largest impact on TC comes from education with an elasticity of 0.16. This large education elasticity is particularly noteworthy since it only measures the residual effect of education after adjusting for educational differences in the labor force. These large elasticities are followed in turn by public research, health care access, and private research. The negative elasticity of private research spill-in on TC is quite large, -0.14.

These findings are consistent with Reimers and Klasen's (2013) finding that education plays an important role in productivity growth through enhancing better decision skills for farmers, improved access to information, and faster adoption of new technologies. Our finding that research investment, both within the state and public research by its regional neighbors, promote technical change is consistent with Alston et al.'s (2011) and Plastina and Fulginiti's (2012) findings of the importance of public research and public research spill-in on agricultural productivity. What is new about our findings is the discovery that health care access also plays a positive and significant role in enhancing technical change. This broadens the set of options available to policy makers for stimulating technical change and productivity growth in the agricultural sector.

Results from the TEC model show a negative and statistically significant effect of health care access, family-to-total labor ratio, and damaging degree days in the central band of states and a positive and statistically significant effect of extension and precipitation on TEC. Education, farm size, and growing degree days do not have a significant effect. Although the estimated impacts of health care access, family-to-total labor ratio, and damaging degree days are small, their negative effects on TEC imply that it is positively affected by a decrease in health care access, relatively larger hired labor work force, and less extreme temperatures. A possible explanation for the first finding could be that limited health care access results in farmers hiring additional labor or other service providers who may be in better health than they are. Although conjectural, this explanation can be supported by the second finding which implies that family labor contributes more to technical efficiency when it is augmented by additional hired labor. This could be due to less burden on family labor enabling it to focus more on management thereby improving managerial efficiency and improving decision making skills. Another possible explanation could be the level of specialization – hired labor may be more skilled in the tasks they are hired to do and hence may be more efficient than family labor. The negative relationship between damaging degree days and TEC is consistent with Key and Sneeringer's (2014) finding that heat stress has a negative effect on technical efficiency on dairies in the U.S.

The SMEC model estimates reveal that farm size, precipitation (at the 0.10 level of significance), growing degree days, and agro-temperature all have positive and statistically significant impact on scale and mix efficiency change. Damaging degree days has a small but significant negative impact on SMEC in the central band of states and a greater negative impact in the southern band of states. Agro-precipitation also has a large and significant negative impact on SMEC in the southern band of states. Agro-temperature has the largest impact on SMEC with a 1 percent increase resulting in 0.34 percent increase in SMEC in the central band of states. This implies that an increase in long-term (50-year) average temperature has been beneficial for SMEC in the mid-latitude states. This finding is not significantly different in either of the other bands of states. This could be a result of farmers moving to more nearly optimal scale as the temperature has increased (a little less than 2°F over the last century). Since growing degree days have a much greater positive effect on SMEC than the negative effect of damaging degree days, another possible explanation could be that the effect of additional growing degree days caused by the increase in agro-temperature has more than offset the effect of additional damaging degree days.

The large positive impact on SMEC of agro-temperature is followed in turn by the negative impact of agro-precipitation in the southern band of states, the positive impacts of growing degree days, farm size, and precipitation, and the negative impact of damaging degree days. As expected, growing degree days have a positive and statistically significant effect on SMEC as crops have more exposure to optimal growing temperature while damaging degree days have a negative and statistically significant effect on SMEC as exposure to adverse temperatures inhibits growth. Damaging degree days have a larger effect in the warmer southern band than in the central band of states. Additional precipitation generally contributes to plant growth and has a positive and significant effect on SMEC. But in the southern band of states, where precipitation has been increasing over the past century, additional long-term precipitation (agro-precipitation) has a pronounced negative impact. An increase in average farm size increases SMEC by moving toward more optimal scale. This finding is similar to the result of Paul et al. (2004) that small family farms are generally less efficient in terms of their scale of operations than are large farms. Our results also show that the 1983 PIK program negatively and significantly affected SMEC. The R^2 values for all our component models are low – 0.29, 0.02, and 0.17 for TC, TEC and SMEC respectively.

Estimates for the TFPC model are reported in Table 4. The TFPC model includes all explanatory variables included in the component models. As with the component models, most parameters are statistically significant. An increase in agro-temperature for the northern and southern bands of states has the greatest impact on TFPC with elasticities of 0.73 and 0.65, respectively. They are followed by decreasing the family-to-total labor ratio and terms of trade, with elasticities of -0.28 and -0.27, respectively. Increasing growing degree days in the northern band of states and agro-temperature in the central band have a positive impact on TFPC, each with an elasticity of 0.23. Increases in public research, public research spill-in, growing degree days as well as agro-precipitation and precipitation in the central band of states, and health care access also have positive impacts on TFPC, with elasticities ranging from 0.05 to 0.15. Private research and damaging degree days in the southern and central bands of states have negative impacts on TFPC, with elasticities of -0.01 to -0.04.

Health care access, public research, and public research spill-in all have plausible signs – positive and statistically significant. Public research and public research spill-in results are consistent with prior findings of the pivotal role public research plays in increasing agricultural productivity (Huffman and Evenson 2006; Plastina and Fulginiti 2012). Health care access results are consistent with our expectation of the impact of human capital on agricultural productivity through enabling farmers to embrace new innovations as well as to avoid disruption to their decision making skills due to inadequate access to health care.

Although somewhat surprising, the finding that a decrease in private research results in an increase in TFP is similar to results from Huffman (2009). Since private research is conducted mainly by agricultural input suppliers, farmers' investment in these innovations is more costly and their adoption may limit the scale and mix of inputs farmers use. Huffman (2009) finds that private and public research are substitutes. Since innovations from public research are likely to be more affordable than those from private research, less private research and more public research appears to be beneficial to productivity of the agricultural sector. A decrease in the terms of trade (output to input price ratio) creates incentive to conserve inputs and increase average productivity, a finding that is consistent with O'Donnell (2010). The findings of both the TFPC and TEC equations are consistent in finding that an increase in hired labor makes all labor more productive.

Parameter estimates for most of the weather and agro-climate variables are statistically significant and have generally plausible signs. The only exception, which is the same as in the SMEC model, is that agro-temperature has a very large positive effect on TFPC for all bands of states. Some prior research (e.g. Lobell and Field 2007; Hatfield et al. 2011) find a negative relationship between an increase in average growing temperature and yields. However, adaptation such as early planting, conservation tillage, and improved planting equipment may be helping to drive gains in yields from this long-term increase in temperature. For example, Sacks and Kucharik (2011) note that corn and soybeans have been planted increasingly earlier over the past 30 years. As expected, an increase in growing degree days (in the northern and central bands) results in an increase in TFPC as crops have more exposure to optimal growth temperature. Also the negative and statistically significant effect of damaging degree days on TFPC is consistent with expectations. Damaging degree days hinder crop growth and lead to a decrease in output. And, the marginal effect is greatest in the warmest region. This result is similar to McCarl et al.'s (2008) finding.

Neither education nor extension have a significant effect on TFPC. With regard to education, this implies that the adjustment of the labor input series to account for changes in education fully exhausts the educational effect on TFPC. The insignificant effect of extension is a greater surprise.

Comparing TFPC elasticities

We next compare TFPC elasticities calculated from the component models to those obtained directly from the estimated TFPC model. These elasticities are presented in Table 5. We report elasticities only for the 15 continuous variables without dummy variable interaction.

Most of the qualitative implications of the elasticities from the components are consistent with those from the elasticities calculated directly from the TFPC model. Parameter estimates for health care access, public research, public research spill-in, family-to-total labor ratio, precipitation, growing degree days, damaging degree days, and agro-temperature all have the same sign and are statistically significant in both approaches. Private research is statistically significant in both approaches but has a different sign, and education, private research spill-in, farm size, terms of trade, and agro-precipitation are significant in only one of the two approaches. Extension remains insignificant regardless of which approach is used. Additionally, there is a big difference in magnitude of a few elasticities between the two approaches. For example, public research spill-in has the highest elasticity from the component models and is over four times as large as when it is computed directly from the TFPC model. The opposite is true for the family-to-total labor ratio and precipitation which are 28 and eight times as large, respectively, in the directly estimated TFPC model than when calculated from the component models.

To check the robustness of our results to the choice of functional form, we also re-estimate the TFPC model in linear form and calculate elasticities at the data means to compare with elasticities from the logarithmic TFPC model. Results are presented in Table 6. Again, most of the qualitative implications are the same. Eight elasticities are statistically significant in both models and have the same sign, four elasticities are insignificant in both specifications, three elasticities are significant in only one model and one elasticity is significant in both models but has a different sign. With the exception of public research spill-in, the elasticity estimates that are significant in both specifications with the same sign are similar in magnitude. Thus, the results do not appear to be highly sensitive to our choice of functional form.

Conclusions

This article has sought a deeper understanding of the drivers of total factor productivity change (TFPC) in U.S. agriculture by examining the drivers of the components of TFPC – technical change, technical efficiency change, and scale and mix efficiency change. Building on O'Donnell's (2012) recent decomposition of U.S. agricultural TFPC into these components, we use economic theory, previous literature, and logic to identify factors potentially driving each component. We also include a broader set of factors potentially driving TFPC than most previous analyses by including health care access, weather, and agro-climatic conditions. We use a state-level panel dataset for the

48 contiguous states for the period 1961-2003 and examine the robustness of implications from the component models with a directly estimated TFPC model using alternative functional forms.

We find that public research conducted within the state as well as spill-ins from the same geo-climatic region, education, and health care access are the main factors driving technical change, which in turn is the dominant component of TFP change. In fact, technical change has much greater impact on TFP change than profit-maximizing output and input choices of firms. These results are consistent with the notion that technical change comes from innovation resulting from R&D and improved human capital which helps in adoption of new innovations. We find private research to have mixed effects on technical change, depending on whether it is patented within the state or in other states in the same geo-climatic region.

Although technical efficiency change is very stable over the data period, changes that do occur are driven primarily by extension, the ratio of family-to-total labor, health care access, and weather (except growing degree days). Technical efficiency change increases as health care access decreases. This unexpected result could be due to farmers hiring additional labor or other service providers who may be in better health than they are. Although theoretical expectations are ambiguous, the impact of the ratio of family-to-total labor is also opposite to conventional wisdom in that technical efficiency change increases as this ratio decreases. This could be because hired labor provides higher skill levels in specialized tasks than do family labor, and/or because family labor focuses more on management thereby improving managerial efficiency and decision making skills when more labor is hired. Education, farm size, and growing degree days do not significantly affect technical efficiency.

Scale and mix efficiency change exhibits considerable fluctuation over the data period but, like technical efficiency change, has little trend. It is affected most by farm size, weather, and agro-climatic conditions. Rising long-term temperatures and larger farm size are both beneficial for scale and mix efficiency change. Government policies such as the 1983 PIK program also have an impact on farmers' scale and mix efficiency change.

With few exceptions, elasticities estimated with the TFPC model are qualitatively the same and similar in magnitude to those calculated from the component models. They are also largely consistent with elasticities computed at data means from a linear TFP model. These results substantiate the important role of public research, health care access, family-to-total labor ratio, weather, and agro-climatic conditions on TFPC of U.S. agriculture.

The results from this study contribute to the policy debate about how to surmount the recent downturn in agricultural productivity. Technical change is the primary component driving total factor productivity growth. Public policy can impact its growth rate most through investment in public research and facilitating additional education and health care access in rural areas.

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Figure 1. U.S. agricultural total factor productivity (TFPC), technical change (TC), technical efficiency change (TEC) and scale and mix efficiency change (SMEC) 1961-2003

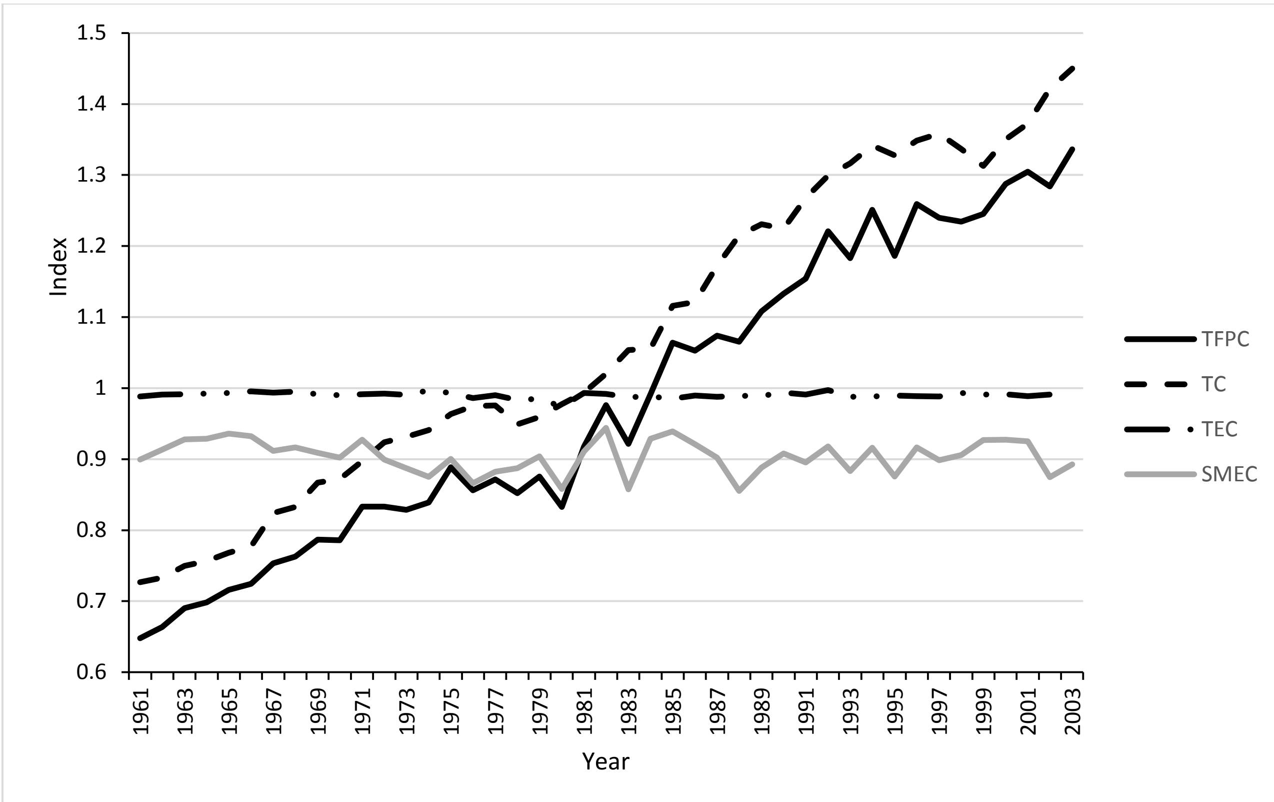

Table 1. Summary Statistics

Variable	Variable Code	Unit	Mean	Standard Deviation	Minimum Value	Maximum Value
Total factor productivity change	*TFPC*	index	0.982	0.301	0.401	2.155
Technical change	*TC*	index	1.072	0.272	0.626	1.869
Technical efficiency change	*TEC*	index	0.990	0.034	0.710	1.000
Scale and mix efficiency change	*SMEC*	index	0.904	0.159	0.407	1.123
Education	*Ed*	index	2.860	0.587	1.411	3.830
Health care access	*Hs*	index	12.013	5.210	4.757	37.318
Public research investment	*Rpub*	$M	15.349	13.775	1.040	101.167
Public research spill-in	*RpubS*	$M	63.947	34.027	5.960	171.737
Private research	*Rpri*	patents	24.187	36.128	0.138	227.997
Private research spill-in	*RpriS*	patents	103.880	93.571	0.773	352.382
Extension	*Ext*	FTE prof. staff	137.157	97.077	0.028	562.310
Farm size	*Fs*	$1,000 per farm	353.230	312.637	15.116	3496.001
Family-to-total labor ratio	*Ftlratio*	index	0.706	0.161	0.112	0.934
Terms of trade	*TT*	index	0.751	0.264	0.279	1.363
Precipitation	*Precp*	cm	36.188	14.958	5.370	80.580
Growing degree days	*GDD*	^{o}F days	2317.183	722.394	1152.947	4456.675
Damaging degree days	*DDD*	^{o}F days	16.586	29.677	0.0001	235.083
Agro-temperature	*Agrotemp*	^{o}F	60.969	6.534	50.616	75.663
Agro-precipitation	*Agroprecp*	cm	35.233	13.605	8.180	58.220

Table 2. Data Diagnostic Tests for the Technical Change (TC), Technical Efficiency Change (TEC), Scale and Mix Efficiency Change (SMEC), and Total Factor Productivity Change (TFPC) Models

Test	Distribution	Null Hypothesis	Test Statistic	P-Value
Technical Change				
Wooldridge (test for autocorrelation)	F(1, 47)	No first-order autocorrelation	597.163	0.000
Modified Wald (test for heteroskedasticity)	$\chi^2(48)$	$\sigma_i^2 = \sigma^2 \forall i$	7209.01	0.000
Hausman (test for regional FE vs RE)	$\chi^2(8)$	Difference in coefficients not systematic	373.87	0.000
Technical Efficiency				
Wooldridge (test for autocorrelation)	F(1, 47)	No first-order autocorrelation	6.667	0.0130
Modified Wald (test for heteroskedasticity)	$\chi^2(48)$	$\sigma_i^2 = \sigma^2 \forall i$	1.7e+06	0.000
Hausman (test for regional FE vs RE)	$\chi^2(14)$	Difference in coefficients not systematic	7.51	0.8221
Scale and Mix Efficiency				
Wooldridge (test for autocorrelation)	F(1, 47)	No first-order autocorrelation	46.368	0.000
Modified Wald (test for heteroskedasticity)	$\chi^2(48)$	$\sigma_i^2 = \sigma^2 \forall i$	2052.96	0.000
Hausman (test for regional FE vs RE)	$\chi^2(17)$	Difference in coefficients not systematic	101.22	0.000
Total Factor Productivity				
Wooldridge (test for autocorrelation)	F(1, 47)	No first-order autocorrelation	34.360	0.000
Modified Wald (test for heteroskedasticity)	$\chi^2(48)$	$\sigma_i^2 = \sigma^2 \forall i$	396.03	0.000
Hausman (test for regional FE vs RE)	$\chi^2(24)$	Difference in coefficients not systematic	118.230	0.000

Note: σ^2 is residual variance, FE is fixed effects, and RE is random effects.

Table 3. Prais-Winsten Estimates for Technical Change (TC), Technical Efficiency (TEC), and Scale and Mix Efficiency (SMEC)

Regressor	Dependent Variable: ln(TC)		Dependent Variable: ln(TEC)		Dependent Variable: ln(SMEC)	
	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error
ln(Education)	0.155*	0.0864	-0.00488	0.00823		
ln(Health care access)	0.0345**	0.0152	-0.00830*	0.00434		
ln(Public research)	0.0799***	0.0142				
ln(Public research spill-in)	0.416***	0.0625				
ln(Private research)	0.0277***	0.00976				
ln(Private research spill-in)	-0.137***	0.0348				
ln(Extension)			0.00353*	0.00208		
ln(Farm size)			0.00122	0.00321	0.0470**	0.0201
ln(Family-to-total labor ratio)			-0.0103**	0.00427		
ln(Terms of trade)					0.00142	0.0295
ln(Precipitation)			0.00604**	0.00282	0.0262*	0.0146
ln(Growing degree days)			0.0112	0.00793	0.110***	0.0307
ln(Damaging degree days)			-0.00290***	0.000602	-0.00897***	0.00216
ln(Agro-temperature)					0.337**	0.142
ln(Agro-precipitation)					0.0251	0.0365
ln(Private research) $*D_{96}$	-0.0129***	0.00397				
ln(Private research spill-in) $*D_{96}$	0.0110**	0.00539				
(lnGDD)$*D_s$			-0.000529	0.000716	-0.0292	0.119
(lnGDD)$*D_n$			0.00000441	0.000508	-0.0460	0.0605
(lnDDD)$*D_s$			0.00221**	0.00107	-0.0230***	0.00800
(lnDDD)$*D_n$			0.00267***	0.000779	0.00384	0.00355
ln(Agro-precipitation)$*D_s$					-0.247***	0.0794
ln(Agro-precipitation)$*D_n$					-0.000618	0.182
ln(Agro-temperature)$*D_s$					0.286	0.233
ln(Agro-temperature)$*D_n$					0.251	0.244
D_{83}					-0.0797***	0.0187

Northeast	0.527***	0.0902			-0.759	0.820
Southeast	0.106*	0.0548			-0.229***	0.0416
North Plains	0.268***	0.0650			-0.635	0.816
South Plains	0.0327	0.0635			-0.110**	0.0437
Mountains	0.223***	0.0640			-0.132***	0.0384
Pacific	0.500***	0.0505			-0.129***	0.0332
Intercept	-8.609***	1.089	-0.117**	0.0596	-2.696***	0.443
Number of observations	2064		2064		2064	
R^2	0.293		0.022		0.168	

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4. Prais-Winsten Estimates for Total Factor Productivity Change (TFPC)

Regressor	Dependent Variable: ln(TFPC)	
	Estimated Coefficient	Standard Error
ln(Education)	0.0883	0.0643
ln(Health care access)	0.0532**	0.0221
ln(Public research)	0.149***	0.0148
ln(Public research spill-in)	0.0931**	0.0405
ln(Private research)	-0.0275***	0.00767
ln(Private research spill-in)	0.0148	0.0215
ln(Extension)	0.00461	0.00737
ln(Farm size)	0.0248	0.0227
ln(Family-to-total labor ratio)	-0.284***	0.0252
ln(Terms of trade)	-0.271***	0.0442
ln(Precipitation)	0.0534***	0.0175
ln(Growing degree days)	0.121***	0.0316
ln(Damaging degree days)	-0.0104***	0.00259
ln(Agro-temperature)	0.232*	0.132
ln(Agro-precipitation)	0.0957**	0.0413
ln(Private research) *D_{96}	-0.00469	0.00658
ln(Private research spill-in) *D_{96}	0.00827	0.00710
(lnGDD)*D_s	-0.121	0.114
(lnGDD)*D_n	0.109*	0.0558
(lnDDD)*D_s	-0.0309***	0.00728
(lnDDD)*D_n	0.000826	0.00332
ln(Agro-precipitation)*D_s	-0.174**	0.0705
ln(Agro-precipitation)*D_n	-0.104	0.143
ln(Agro-temperature)*D_s	0.420*	0.226
ln(Agro-temperature)*D_n	0.499***	0.172
D_{83}	-0.0854***	0.0261
Northeast	-2.384***	0.728
Southeast	-0.0953***	0.0367
North Plains	-2.368***	0.716
South Plains	-0.189***	0.0452
Mountains	0.0238	0.0491
Pacific	0.0413	0.0369
Intercept	-6.972***	0.886
Number of observations	2064	
R^2	0.643	

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5. TFPC Elasticities Calculated from Component Models and Estimated Directly from the Total Factor Productivity Change Model

	Component Models		TFPC Model	
	Elasticity	Standard Error	Elasticity	Standard Error
ln(Education)	0.150*	0.0864	0.0883	0.0643
ln(Health care access)	0.0262*	0.0158	0.0532**	0.0221
ln(Public research)	0.0799***	0.0142	0.149***	0.0148
ln(Public research spill-in)	0.416***	0.0625	0.0931**	0.0405
ln(Private research)	0.0277***	0.00976	-0.0275***	0.00767
ln(Private research spill-in)	-0.137***	0.0348	0.0148	0.0215
ln(Extension)	0.00353	0.00208	0.00461	0.00737
ln(Farm size)	0.0482**	0.0204	0.0248	0.0227
ln(Family-to-total labor ratio)	-0.0103**	0.00427	-0.284***	0.0252
ln(Terms of trade)	0.000239	0.03	-0.271***	0.0442
ln(Precipitation)	0.00604**	0.00282	0.0534***	0.0175
ln(Growing degree days)	0.121***	0.0317	0.121***	0.0316
ln(Damaging degree days)	-0.0119***	0.00224	-0.0104***	0.00259
ln(Agro-temperature)	0.337**	0.142	0.232*	0.132
ln(Agro-precipitation)	0.0251	0.0365	0.0957**	0.0413

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6. TFPC Elasticities Estimated Directly from the Logarithmic TFPC Model and Calculated at Data Means from the Linear TFP Model

	ln(TFPC) Model		Linear TFPC Model	
	Elasticity	Standard Error	Elasticity	Standard Error
Education	0.0883	0.0643	-0.0054	0.0773
Health care access	0.0532**	0.0221	0.0735***	0.0223
Public research	0.149***	0.0148	0.1558***	0.0159
Public research spill-in	0.0931**	0.0405	0.1972***	0.0430
Private research	-0.0275***	0.00767	-0.0228***	0.0083
Private research spill-in	0.0148	0.0215	-0.0458	0.0282
Extension	0.00461	0.00737	0.0132	0.0146
Farm size	0.0248	0.0227	0.0055	0.0041
Family-to-total labor ratio	-0.284***	0.0252	-0.3535***	0.0355
Terms of trade	-0.271***	0.0442	-0.2034***	0.0416
Precipitation	0.0534***	0.0175	0.0493***	0.0187
Growing degree days	0.121***	0.0316	-0.0383	0.0364
Damaging degree days	-0.0104***	0.00259	0.0057	0.0045
Agro-temperature	0.232*	0.132	0.1169	0.1350
Agro-precipitation	0.0957**	0.0413	0.1577***	0.0600

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$