Decomposing U.S. Agricultural Productivity into Weather Shocks, Technical Change, Scale Effects, Input Price Effects, and Cost Efficiency

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Understanding the major drivers of U.S. agricultural productivity is critical for policy makers interested in developing policies to support food security and a healthy farm economy, and to maintain the relevance of the United States in global agricultural commodity markets. Several studies have analyzed the contribution of technical change, scale effects, price effects, and efficiency to U.S. agricultural productivity. However, despite the major role of short-term weather variability as a source of production risk, only two studies have analyzed the link between U.S. agricultural productivity and weather at the state level. Ortiz-Bobea, Knippenberg, and Chambers (2018) combine U.S. state-level measures of total factor productivity (TFP) with detailed climate data and find that agriculture is growing more sensitive to weather variability in Midwestern states, due mainly to the compounding effect of a growing specialization in crop production and a rising sensitivity to climate of non-irrigated row-crop production. In addition, Njuki, Bravo-Ureta, and O'Donnell (2018) use an axiomatic approach to decompose TFP growth in U.S. agriculture into weather effects, technological progress, technical efficiency, and scale and mix efficiency changes. That study concludes that, on average, annual weather effects have had a negative, albeit negligible, impact on TFP growth (although substantial heterogeneity in weather effects were observed across states and time).

The objective of this study is threefold. First, we evaluate the contribution of weather shocks, technical change, scale effects, input price effects, and cost efficiency to TFP growth in U.S. agriculture using state-level production and climate data for states in the Central (Iowa, Illinois, Indiana, Michigan, Missouri, Minnesota, Ohio, and Wisconsin) and Pacific (California, Oregon, and Washington) regions over 1964-2004. Second, we evaluate the percent change in agricultural productivity due to weather shocks by constructing indexes of TFP (in levels) under the assumption of no weather shocks, and compare these with the corresponding indexes published by USDA (2017). Third, we assess the bias in the estimated individual contributions of each of the components of TFP when failing to account for weather shocks, by comparing the estimates from the main model with an alternative TFP growth model on the original (not-weather-filtered) production variables.

The novel parametric framework of analysis developed in this article consists of a two-stage model that first estimates weather effects on inputs and outputs of production following Ortiz-Bobea, Knippenberg, and Chambers (2018), and then estimates TFP growth on “weather-filtered” production variables following an expanded version of the algorithm developed by Plastina and Lence (2018).

We are able to measure the monetary impact of abnormal weather in agriculture by state, and examine its temporal pattern. In particular, we are interested in evaluating whether the monetary impact of abnormal weather differs between the first half and the second half of the sample.

Methodological Framework

Decomposing TFP Change with Quasi-Fixed Inputs and Weather Effects

The official USDA (2017) index of TFP for state *s* in year *t* relative to Alabama in 1996 is calculated as:

$$(1)\ TFP_{st} = \frac{Y_{st}}{X_{st}} \frac{X_{AL\ 1996}}{Y_{AL\ 1996}},$$

where Y and X indicate, respectively, total farm output and total farm input, defined as the implicit quantity indexes $Y \equiv \sum_n p_n Y_n / P$ and $X \equiv \sum_j w_j X_j / W$; where p_n and Y_n are, respectively, the price index and the quantity index for the *n*-th output; w_j and X_j are, respectively, the price index and the quantity index for the *j*-th input; and P and W are, respectively, the price indexes for total farm output and total farm input. Log-differencing (1) with respect to time, and dropping the state and time subscripts to reduce cluttering, the instantaneous change in TFP through time can be expressed as:

$$(2)\ T\dot{F}P = \dot{Y} - \sum_i \frac{w_{v_i} X_{v_i}}{C_o(w,X)} \left(\dot{w}_{v_i} + \dot{X}_{v_i}\right) - \sum_g \frac{w_{q_g} X_{q_g}}{C_o(w,X)} \left(\dot{w}_{q_g} + \dot{X}_{q_g}\right) + \dot{W},$$

where a dot over a variable indicates percentage change through time,[1] $C_o(w, X) = \sum_i w_{v_i} X_{v_i} + \sum_g w_{q_g} X_{q_g}$ is the observed cost of production, X_v denotes variable inputs, and X_q represents quasi-fixed inputs (i.e., inputs cannot be fully adjusted according to the observed relative prices between two consecutive periods).

Define short-term overall cost efficiency, $OCE(\underline{Y}, w_v, X_v; X_q; t)$, as the product of technical efficiency, $TE(\underline{Y}, X_v; X_q; t)$, and allocative efficiency, $AE(\underline{Y}, w_v, X_v; X_q; t)$, such that (Farrell, 1957):

$$(3)\ 0 < OCE(\underline{Y}, w_v, X_v; X_q; t) \equiv TE(\underline{Y}, X_v; X_q; t) \times AE(\underline{Y}, w_v, X_v; X_q; t) \equiv C(\underline{Y}, w_v; X_q; t)/C_v(w_v, X_v) \leq 1,$$

where $\underline{Y}$ is the vector of observed outputs, the observed variable cost of production is $C_v(w_v, X_v) = \sum_i w_{v_i} X_{v_i}$, and the (unobserved) short-run minimum cost of production is $C(\underline{Y}, w_v; X_q; t)$. Log-differencing $OCE(\underline{Y}, w_v, X_v; X_q; t)$ with respect to time yields:

$$(4)\ \dot{TE} + \dot{AE} = \sum_n \frac{\partial \ln C(\underline{Y}, w_v; X_q; t)}{\partial \ln Y_n} \dot{Y}_n + \sum_i \frac{\partial \ln C(\underline{Y}, w_v; X_q; t)}{\partial \ln w_{v_i}} \dot{w}_{v_i} + \sum_g \frac{\partial \ln C(\underline{Y}, w_v; X_q; t)}{\partial \ln X_{q_g}} \dot{X}_{q_g} + \frac{\partial \ln C(\underline{Y}, w_v; X_q; t)}{\partial t} - \sum_i \frac{w_{v_i} X_{v_i}}{C_v(w_v, X_v)} (\dot{w}_{v_i} + \dot{X}_{v_i}),$$

Upon rearrangement, by replacing the last term of (4) into (3) TFP change can be expressed as:

$$(5)\ \dot{TFP} = \dot{Y} - \sum_g s_{q_g} \left(\dot{w}_{q_g} + \dot{X}_{q_g}\right) + \dot{W} + \frac{C_v(w_v, X_v)}{C_o(w, X)} \Big\{TC + \dot{TE} + \dot{AE} - \sum_n \varepsilon_{CY_n}(\underline{Y}, w_v; X_q; t)\, \dot{Y}_n - \sum_g \varepsilon_{CX_{q_g}}(\underline{Y}, w_v; X_q; t)\, \dot{X}_{q_g} - \sum_i s^*_{v_i}(\underline{Y}, w_v; X_q; t)\, \dot{w}_{v_i}\Big\},$$

where $s_{q_g} \equiv \frac{w_{q_g} X_{q_g}}{C_o(w, X)}$ is the observed total cost share of quasi-fixed input g; $s_{v_i} \equiv \frac{w_{v_i} X_{v_i}}{C_v(w_v, X_v)}$ is the observed variable cost share of variable input i; $s^*_{v_i}(\underline{Y}, w_v; X_q; t) \equiv \frac{\partial \ln C(\underline{Y}, w_v; X_q; t)}{\partial \ln w_{v_i}}$ is the (unobserved) minimum cost share of variable input i; $TC \equiv -\frac{\partial \ln C(\underline{Y}, w_v; X_q; t)}{\partial t}$ is technical change;

[1] For variables observed at discrete intervals, these instantaneous changes are approximated as: $\dot{X} = \ln X_t - \ln X_{t-1}$.

$\varepsilon_{CY_n}\left(\underline{Y}, w_v; X_q; t\right) \equiv \frac{\partial \ln C\left(\underline{Y}, w_v; X_q; t\right)}{\partial \ln Y_n}$ is the cost elasticity with respect to output Y_n; and

$\varepsilon_{CX_{q_g}}\left(\underline{Y}, w_v; X_q; t\right) \equiv \frac{\partial \ln C\left(\underline{Y}, w_v; X_q; t\right)}{\partial \ln X_{q_g}}$ is the cost elasticity with respect to quasi-fixed input X_{q_g}.

Furthermore, after some algebraic manipulation, and defining the change in observed revenue-weighted output as $\dot{Y}_R \equiv \sum_n R_n \dot{Y}_n$, the observed revenue share of the *n*-th output as $R_n \equiv p_n Y_n / \sum_m p_m Y_m$, the changes in minimum short-run costs induced by changing output quantities as $\dot{Y}_C \equiv \sum_n \varepsilon_{CY_n}\left(\underline{Y}, w_v; X_q; t\right)\dot{Y}_n$, and returns to scale as $RTS \equiv 1/\sum_n \varepsilon_{CY_n}\left(\underline{Y}, w_v; X_q; t\right)$, TFP change can be re-written as:

$$(6)\ T\dot{F}P = \left(\dot{Y}_R - \frac{C_v(w_v, X_v)}{C_o(w,X)}\ \dot{Y}_C\right) + \frac{C_v(w_v, X_v)}{C_o(w,X)}(1 - RTS^{-1})\ \dot{Y}_C - \sum_g \left\{s_{q_g} + \frac{C_v(w_v, X_v)}{C_o(w,X)} \varepsilon_{CX_{q_g}}\left(\underline{Y}, w_v; X_q; t\right)\right\} \dot{X}_{q_g} - \frac{C_v(w_v, X_v)}{C_o(w,X)} \sum_i \left\{s^*_{v_i}\left(\underline{Y}, w_v; X_q; t\right) - s_{v_i}\right\}\dot{w}_{v_i} + \left(\sum_n R_n \dot{p}_n - \dot{P}\right) - \left\{\sum_i \frac{w_{v_i} X_{v_i}}{C_o(w,X)} \dot{w}_{v_i} - \sum_g \frac{w_{q_g} X_{q_g}}{C_o(w,X)} \dot{w}_{q_g} - \dot{W}\right\} + \frac{C_v(w_v, X_v)}{C_o(w,X)}\left\{TC + T\dot{E} + A\dot{E}\right\},$$

$$(7)\ T\dot{F}P\ = MUE + SE - QFIE - IPF + OPAE - IPAE + \frac{C_v(w_v, X_v)}{C_o(w,X)}\left\{TC + T\dot{E} + A\dot{E}\right\}.$$

Equations (6) and (7) collapse to the expression described by Bauer (1990), and applied by Plastina and Lence (2018) in the analysis of agricultural productivity in 32 states of the United States, when all inputs are variable (i.e., no quasi-fixed inputs exist). Therefore, Bauer (1990) is a special case of the present framework. The term $MUE \equiv \left(\dot{Y}_R - \frac{C_v(w_v, X_v)}{C_o(w,X)} \dot{Y}_C\right)$ denotes the markup effect, as it captures the contribution of non-marginal-cost pricing to productivity change: the greater the market power to set output prices above marginal costs, the faster TFP will increase. Under marginal-cost pricing such that $p_n = \frac{C_v(w_v, X_v)}{C_o(w,X)} \frac{\partial C_v\left(\underline{Y}, w_v; X_q; t\right)}{\partial Y_n}$ and $R_n = \frac{C_v(w_v, X_v)}{C_o(w,X)} \varepsilon_{CY_n}\left(\underline{Y}, w_v; X_q; t\right)$, the markup effect becomes null. The term $SE \equiv \frac{C_v(w_v, X_v)}{C_o(w,X)}(1 - RTS^{-1})\dot{Y}_C$ represents the scale effect, reflecting the short-term productivity changes stemming from changes in the scale of production.[2] The term $QFIE \equiv \sum_g \left\{s_{q_g} + \frac{C_v(w_v,X_v)}{C_o(w,X)} \varepsilon_{CX_{q_g}}\left(\underline{Y}, w_v; X_q; t\right)\right\} \dot{X}_{q_g}$ is the quasi-fixed input effect, measured as the sum of the change in observed total cost and the change in short-term costs due to marginal changes in the levels of the quasi-fixed inputs. The term $IPF \equiv \frac{C_v(w_v,X_v)}{C_o(w,X)} \sum_i \left\{s^*_{v_i}\left(\underline{Y}, w_v; X_q; t\right) - s_{v_i}\right\} \dot{w}_{v_i}$ is the input price factor, and measures the effect of input price changes on productivity, weighted by the differences between the observed cost shares and the short-term cost-minimizing shares. The input price factor is null when market prices equal shadow values for all variable inputs. The fifth and sixth terms in the above equations are, respectively, the output price aggregation effect, $OPAE \equiv \left(\sum_n R_n \dot{p}_n - \dot{P}\right)$, and the input price aggregation effect, $IPAE \equiv \left(\sum_i \frac{w_{v_i} X_{v_i}}{C_o(w,X)} \dot{w}_{v_i} - \sum_g \frac{w_{q_g} X_{q_g}}{C_o(w,X)} \dot{w}_{q_g} - \dot{W}\right)$, which are residuals arising from the methods applied by USDA (2017) to calculate the quantity indexes. TC measures the inter-annual reduction in the minimum-cost combination of inputs required to produce the observed level of output, keeping input prices constant.[3] In this framework, technological progress (regress) occurs when $TC > 0$ ($TC < 0$). $\dot{TE}$ quantifies the inter-annual change in the proportional overuse of all inputs. Improvements (deteriorations) in technical efficiency are the result of declining (increasing) proportional overuse of all inputs, and are reflected in the model as $\dot{TE} > 0$ ($\dot{TE} < 0$). $\dot{AE}$ measures the inter-annual change in the gap between the observed cost and the minimum cost in each year. A reduction (an increase) in the gap between the observed cost and the minimum cost through time enhances (worsens) allocative efficiency, leading to $\dot{AE} > 0$ ($\dot{AE} < 0$) in the model.

To incorporate weather effects into the analysis, we let the superscript e indicate the (unobserved) state for a production variable under “normal” weather conditions, and define $Y^e \equiv$

[2] When the scale of operation is optimal this term becomes null, because $RTS = 1$.
[3] Note that a minimum-cost combination of inputs is a theoretical construct based on the observed prices and output produced with a specific technology. The minimum cost is typically different from the observed cost to produce such level of output due to productive or allocative inefficiency.

$\sum_n p_n^e Y_n^e / P^e$ and $X^e \equiv (\sum_i w_{v_i}^e X_{v_i}^e + \sum_g w_{q_g}^e X_{q_g}^e)$, such that the weather effects on aggregate output and aggregate input are measured, respectively, as $\gamma \equiv \frac{Y}{Y^e} \geq 0$ (for $Y^e > 0$) and $\delta \equiv \frac{X}{X^e} \geq 0$ (for $X^e > 0$). When $\gamma > (<)\ 1$, abnormal weather conditions are beneficial (detrimental) to agricultural production, as observed output exceeds (falls short of) the predicted output under normal weather conditions. Similarly, when $\delta < (>)\ 1$, abnormal weather conditions are favorable (adverse) to agricultural production, because observed input use is smaller (larger) than predicted input use under normal weather conditions. Note that the annual percent change in aggregate output, $\dot{Y}$, can be decomposed into changes in output under "normal" weather conditions, $\dot{Y}^e$, and annual shocks due to "abnormal" weather conditions, $\dot{\gamma}$: $\dot{Y} \equiv \dot{Y}^e + \dot{\gamma}$. Similarly, the annual percent change in aggregate input use, $\dot{X}$, can be decomposed into a change in input use under "normal" weather conditions, $\dot{X}^e$, and a change in the deviations due to "abnormal" weather conditions, $\dot{\delta}$: $\dot{X} \equiv \dot{X}^e + \dot{\delta}$. Defining the net weather effect on TFP change as $NWEFF \equiv (\dot{\gamma} - \dot{\delta})$, the weather-filtered TFP change, $\dot{TFP}^{WF}$, can be calculated as:

$$(8)\ \dot{TFP}^{WF} = \dot{TFP} - NWEFF$$
$$= MUE^e + SE^e - QFIE^e - IPF^e + OPAE^e - IPAE^e + \frac{C_v^e(w_v^e, X_v^e)}{C_O^e(w^e, X^e)}\{TC^e + \dot{TE}^e + \dot{AE}^e\}.$$

Abnormal weather effects foster (hinder) TFP change if $NWEFF > (<)\ 0$, as the observed rate of TFP change is larger (smaller) than the rate of weather-filtered TFP change, i.e. $\dot{TFP} > (<)\ \dot{TFP}^{WF}$. The present methodological framework complements previous studies highlighting the increased sensitivity of agricultural productivity to weather variability (Ortiz-Bobea, Knippenberg, and Chambers 2018) by providing an actual measure of the impact of weather effects on productivity change. Furthermore, while previous studies provided aggregate measures of weather effects on TFP change (Njuki, Bravo-Ureta, and O'Donnell, 2018), the proposed framework is the first one to calculate a net weather effect on TFP change that can be traced back to the individual weather effects on inputs and outputs by state and year. Our framework will improve our understanding of the varying linkages between weather and agricultural productivity through time and states, and will help inform policy makers about the contribution of the other components to TFP change after accounting for weather effects.

Unfortunately, there is no reasonable way to reconstruct an index of weather-filtered TFP in levels comparable to the official USDA index of TFP by integrating $T\dot{FP}^{WF}$ through time without making a strong assumption about the relative value of both indexes (in levels) at one point in time.[4] However, we are able to introduce a novel measure of the monetary impact of abnormal weather (IAW) on the profitability of the farm sector, namely, the difference between observed profits and (unobserved) estimated profits under "normal" weather conditions:[5]

$$(9)\ IAW = P(Y - Y^e) - W(X - X^e)$$
$$= \sum_n p_n (Y_n - Y_n^e) - \sum_i w_{v_i} \left(X_{v_i} - X_{v_i}^e\right) - \sum_g w_{q_g} \left(X_{q_g} - X_{q_g}^e\right).$$

Higher (lower) observed output than weather-filtered output, i.e. $Y_n > (<)\ Y_n^e$, or lower (higher) observed input than weather-filtered input, i.e. $X_j < (>)\ X_j^e$, results in beneficial (detrimental) abnormal weather events for farm production, i.e. $IAW > (<)\ 0$. Furthermore, by comparing the mean and variance of IAW in the first half versus the second half of the sample, we are able to evaluate the extent to which the impact of abnormal weather on the profitability of the farm sector has remained stable over time.

Econometric Model to Estimate Agricultural Technology

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[4] Mathematically, the problem resides in the unknown value of the arbitrary constant of integration for $\int_{t_0}^{T} T\dot{FP}^{WF}\, dt$.

[5] An alternative formula for the difference between observed profits and (unobserved) estimated profits under "normal" weather conditions is $IAW' = (P^e Y^e - PY) - (W^e X^e - WX)$. This formulation yields the same qualitative results as the ones reported in this study.

Two models are estimated using an input distance function to represent the underlying agricultural technology (Plastina and Lence 2018).[6] Models 1 and 2 are estimated, respectively, using the original USDA production variables, and our weather-filtered variables. TFP change, the net weather effect on TFP change, and the monetary impact of abnormal weather on the profitability of the farm sector are later derived using parameter estimates from Models 1 and 2, and equations (7), (8), and (9). For simplicity, the econometric estimations are only discussed in terms of the original variables. For each region, the estimated model consists of the following translog approximation to the input distance function $D\left(\underline{Y}, X; t\right)$:

$$(10)\quad -x_{v_1 st} = \beta_0 + \sum_{n=1}^{N} \alpha_n\, y_{nst} + \sum_{i=2}^{I} \beta_{v_i}\, \tilde{x}_{v_i st} + \sum_{g=1}^{G} \beta_{q_g}\, x_{q_g st} + \frac{1}{2}\sum_{m=1}^{N} \sum_{n=1}^{N} \alpha_{mn}\, y_{mst}\, y_{nst} + \frac{1}{2}\sum_{i=2}^{I} \sum_{j=2}^{I} \beta_{v_i v_j}\, \tilde{x}_{v_i st}\, \tilde{x}_{v_j st} + \frac{1}{2}\sum_{g=1}^{G} \sum_{h=1}^{G} \beta_{q_g q_h}\, x_{q_g st} x_{q_h st} + \frac{1}{2}\sum_{g=1}^{G} \sum_{i=2}^{I} \beta_{q_g v_i}\, x_{q_g st} \tilde{x}_{v_i st} + \sum_{n=1}^{N} \sum_{i=2}^{I} \delta_{n v_i}\, y_{nst}\, \tilde{x}_{v_i st} + \sum_{n=1}^{N} \sum_{g=1}^{G} \delta_{n q_g}\, y_{nst}\, x_{q_g st} + \sum_{t=1}^{T} \lambda_t d_t \left[1 + \sum_{n=1}^{N} \alpha_{n\Theta}\, y_{nst} + \sum_{i=2}^{I} \beta_{v_i \Theta}\, \tilde{x}_{v_i st} + \sum_{g=1}^{G} \beta_{q_g \Theta}\, x_{q_g st}\right] - \left(\rho_{0s} + \rho_{1s} t + \frac{1}{2}\rho_{2s} t^2\right) + \vartheta_{st},$$

where $x_{v_1 st} \equiv \ln X_{v_1 st}$ is the logarithm of the numeraire (variable) input, $y_{nst} \equiv \ln Y_{nst}$ is the logarithm of the *n*-th output, $x_{q_g st} \equiv \ln X_{q_g st}$ is the logarithm of the g-th quasi-fixed input, $\tilde{x}_{v_i st} \equiv \ln\left(\frac{X_{v_i st}}{X_{v_1 st}}\right)$ is the logarithm of the *i*-th variable input factor ratio, *m* and *n* index outputs, *i* and *j* (*g* and *h*) index variable (quasi-fixed) inputs, $u_{st} = \rho_{0s} + \rho_{1s} t + \frac{1}{2}\rho_{2s} t^2$ is a non-negative term measuring technical inefficiency ($TE_{st} \equiv \exp(-u_{st})$) as a function of time, $t = \{1, \dots, T\}$, s indexes states, and

[6] Duality between the cost function and the input distance function, such that $C\left(\underline{Y}, w_v, X_q; t\right) \equiv \min_{X_{v_i}}\left\{\sum_i w_{v_i} X_{v_i} : D\left(\underline{Y}, X_v, X_q; t\right) \geq 1;\ w_{v_i} > 0; i = 1, \dots, I-1\right\}$, requires the input requirement set to be non-empty, closed, and convex for each output. If all variable input prices are non-negative and some take on non-positive values, then the duality theorem also requires that variable inputs be weakly disposable. Under these assumptions, the input requirement set is completely characterized by the input distance function (Fare and Primont 1995, p. 21).

ϑ_{st} is a normally distributed residual with zero mean and finite variance. The term $\sum_{t=1}^{T} \lambda_t d_t$ is a flexible index of technical change, where d_t is an annual dummy variable (Baltagi and Griffin 1988).

The input distance function is restricted in estimation to be:

a) homogeneous of degree one in the variable inputs, i.e.

(11) $\sum_{i=1}^{I} \beta_{v_i} = 1$;

(12) $\sum_{i=1}^{I} \beta_{v_i v_j} = \sum_{i=1}^{I} \beta_{q_g v_i} = \sum_{i=1}^{I} \delta_{n v_i} = \sum_{i=1}^{I} \beta_{v_i \Theta} = 0$;

b) non-increasing in outputs, i.e.

(13) $\frac{\partial \ln D(Y,X;t)}{\partial y_{mst}} = \alpha_m + \sum_n \alpha_{mn} y_{nst} + \sum_{i=1}^{I} \delta_{m v_i} x_{v_i st} + \sum_{g=1}^{G} \delta_{m q_g} x_{q_g st} + \lambda_t \beta_{m\Theta} \leq 0$;

c) non-decreasing in all inputs (technological characteristic), i.e.

(14) $\frac{\partial \ln D(Y,X;t)}{\partial x_{v_j st}} = \beta_{v_j} + \sum_{i=1}^{I} \beta_{v_i v_j} x_{v_i st} + \sum_{g=1}^{G} \beta_{v_j q_g} x_{q_g st} + \sum_{n=1}^{N} \delta_{n v_j} y_{nst} + \lambda_t \beta_{v_j \Theta} \geq 0$;

(15) $\frac{\partial \ln D(Y,X;t)}{\partial x_{q_h st}} = \beta_{q_h} + \sum_{g=1}^{G} \beta_{q_g q_h} x_{q_g st} + \sum_{i=1}^{I} \beta_{v_i q_h} x_{v_i st} + \sum_{n=1}^{N} \delta_{n q_h} y_{nst} + \lambda_t \beta_{q_h \Theta} \geq 0$;

d) quasi-convex in outputs, i.e.

(16) $\begin{bmatrix} \alpha_{11} & \cdots & \alpha_{1N} \\ \vdots & \ddots & \vdots \\ \alpha_{N1} & \cdots & \alpha_{NN} \end{bmatrix}$ is a positive semi-definite matrix; and

e) concave in variable inputs, i.e.

(17) $\begin{bmatrix} \beta_{v_1 v_1} & \cdots & \beta_{v_1 v_I} \\ \vdots & \ddots & \vdots \\ \beta_{v_I v_1} & \cdots & \beta_{v_I v_I} \end{bmatrix}$ is a negative definite matrix.

Following Plastina and Lence (2018, 2019), to control for the potential endogeneity problem associated with having variable input quantities as regressors in the distance function, we postulate the following regression equation for each of the $(I-1)$ input ratios:

$$(18)\quad \tilde{x}_{v_j st} = \zeta_0^{v_j} + \sum_{n=1}^{N} \varphi_n^{v_j}\, y_{nst} + \sum_{i=1}^{I} \zeta_i^{v_j}\, \ln w_{v_i st} + \sum_{g=1}^{G} \zeta_g^{v_j}\, \ln w_{q_g st} + \frac{1}{2}\sum_{m=1}^{N}\sum_{n=1}^{N} \varphi_{mn}^{v_j}\, y_{mst}\, y_{nst} + \frac{1}{2}\sum_{i=1}^{I}\sum_{g=1}^{G} \zeta_{iq_g}^{v_j} \ln w_{v_i st} \ln w_{q_g st} + \sum_{n=1}^{N}\sum_{i=1}^{I} \varsigma_{nv_i}^{v_j}\, y_{nst}\, \ln w_{v_i st} + \sum_{n=1}^{N}\sum_{g=1}^{G} \varsigma_{nq_g}^{v_j}\, y_{nst}\, \ln w_{q_g st} + \vartheta_{st}^{v_j}, j = 2, \ldots, I,$$

$$(19)\quad x_{q_h st} = \zeta_0^{q_h} + \sum_{n=1}^{N} \varphi_n^{q_h}\, y_{nst} + \sum_{i=1}^{I} \zeta_i^{q_h}\, \ln w_{v_i st} + \sum_{g=1}^{G} \zeta_g^{q_h}\, \ln w_{q_g st} + \frac{1}{2}\sum_{m=1}^{N}\sum_{n=1}^{N} \varphi_{mn}^{q_h}\, y_{mst}\, y_{nst} + \frac{1}{2}\sum_{i=1}^{I}\sum_{g=1}^{G} \zeta_{ig}^{q_h} \ln w_{v_i st} \ln w_{q_g st} + \sum_{n=1}^{N}\sum_{i=1}^{I} \varsigma_{ni}^{q_h}\, y_{nst}\, \ln w_{v_i st} + \sum_{n=1}^{N}\sum_{g=1}^{G} \varsigma_{nq_g}^{q_h}\, y_{nst}\, \ln w_{q_g st} + \vartheta_{st}^{q_h}, h = 1, \ldots, G,$$

and simultaneously estimate (10) and (18)-(19) as a system of $I + G$ equations. In this system, significant correlation between residuals ϑ_{st} and $\vartheta_{st}^{v_j}$, or between residuals ϑ_{st} and $\vartheta_{st}^{q_h}$, provides evidence of endogeneity. That is, if at least one of the $(I - 1) + G$ correlations between residuals ϑ_{st} and the residuals from regressions (18)-(19) is significant, the appropriate estimation consists of the system rather than the single regression.

The minimum cost to produce the output vector $\underline{Y}$ given the input price vector w and technology $D(\underline{Y}, X; t)$ at time *t*, represented by $C(\underline{Y}, w_v; X_q; t)$ can be recovered from the solution to the following optimization problem (Plastina and Lence, 2018):

$$(20)\quad \min_{[\hat{\tilde{x}}_{v_2 st}, \ldots, \hat{\tilde{x}}_{v_I st}]} w_{1st}\, e^{-\hat{p}_{st} - \hat{q}(\hat{\tilde{x}}_{v_2 st}, \ldots, \hat{\tilde{x}}_{v_I st})} \left(1 + \sum_{i=2}^{I} \frac{w_{v_i st}}{w_{v_1 st}}\, e^{\hat{\tilde{x}}_{v_i st}}\right),$$

where a hat over a variable indicates its fitted value, $\hat{X}_{v_1 st} = e^{\hat{x}_{v_1 st}}$, $\hat{X}_{v_i st}/\hat{X}_{v_1 st} = e^{\hat{\tilde{x}}_{v_i st}}$, $\hat{p}_{st} \equiv \hat{\beta}_0 + \sum_{n=1}^{N} \hat{\alpha}_n\, y_{nst} + \sum_{g=1}^{G} \hat{\beta}_{q_g}\, x_{q_g st} + \frac{1}{2}\sum_{m=1}^{N}\sum_{n=1}^{N} \hat{\alpha}_{mn}\, y_{mst}\, y_{nst} + \frac{1}{2}\sum_{g=1}^{G}\sum_{h=1}^{G} \hat{\beta}_{q_g q_h}\, x_{q_g st} x_{q_h st} + \sum_{n=1}^{N}\sum_{g=1}^{G} \hat{\delta}_{nq_g}\, y_{nst}\, x_{q_g st} + \sum_{t=1}^{T} \hat{\lambda}_t d_t \left[1 + \sum_{n=1}^{N} \hat{\alpha}_{n\Theta}\, y_{nst} + \sum_{g=1}^{G} \hat{\beta}_{q_g \Theta}\, x_{q_g st}\right] - \min\{\hat{u}_{st}\}$, and $\hat{q}(\hat{\tilde{x}}_{v_2 st}, \ldots, \hat{\tilde{x}}_{v_I st}) \equiv \sum_{i=2}^{I} \hat{\beta}_{v_i}\, \hat{\tilde{x}}_{v_i st} + \frac{1}{2}\sum_{i=2}^{I}\sum_{j=2}^{I} \hat{\beta}_{v_i v_j}\, \hat{\tilde{x}}_{v_i st}\, \hat{\tilde{x}}_{v_j st} + \sum_{n=1}^{N}\sum_{i=2}^{I} \hat{\delta}_{nv_i}\, y_{nst}\, \hat{\tilde{x}}_{v_i st} + \frac{1}{2}\sum_{g=1}^{G}\sum_{i=2}^{I} \hat{\beta}_{q_g v_i}\, x_{q_g st} \hat{\tilde{x}}_{v_i st} + \sum_{t=1}^{T} \hat{\lambda}_t d_t \sum_{i=2}^{I} \hat{\beta}_{v_i \Theta}\, \hat{\tilde{x}}_{v_i st}$. The solution to the unconstrained optimization (20) yields the estimated minimum cost $\hat{C}\left(\underline{Y}_{st}, w_{vst}; X_{qst}; t\right)$ and the vector of optimal variable input ratio estimates $[\hat{\tilde{x}}^*_{v_2st}, \dots, \hat{\tilde{x}}^*_{v_Ist}]$. The input price factor is then calculated as

$$(21)\quad \widehat{IPF} = \frac{C_v(w_v, X_v)}{C_o(w, X)} \sum_i \left\{\hat{s}^*_{v_i}\left(\underline{Y}, w_v; X_q; t\right) - s_{v_i}\right\} \dot{w}_{v_i} = \frac{C_v(w_v, X_v)}{C_o(w, X)} \sum_i \left\{\frac{w_{v_ist}\, \hat{X}^*_{v_ist}}{\sum_{i=1}^{I} w_{v_ist}\, \hat{X}^*_{v_ist}} - s_{v_i}\right\} \dot{w}_{v_i},$$

where $\hat{s}^*_{v_i}\left(\underline{Y}, w_v; X_q; t\right) \equiv w_{v_ist}\, \hat{X}^*_{v_ist} \big/ \left(\sum_{i=1}^{I} w_{v_ist}\, \hat{X}^*_{v_ist}\right)$ is the estimated cost-minimizing *i*-th variable input share, and $\hat{X}^*_{v_ist}$ is the estimated cost-minimizing level of the *i*-th variable input, which is recovered as[7]

$$(22)\quad \hat{X}^*_{v_ist} = e^{-\hat{p}_{st} - \hat{q}(\hat{\tilde{x}}^*_{v_2st}, \dots, \hat{\tilde{x}}^*_{v_Ist}) + \hat{\tilde{x}}^*_{v_ist}}, i = 1, \dots, I.$$

Recovering Allocative Efficiency Change

Taking the log difference of the short-term overall cost efficiency, $OCE\left(\underline{Y}, w_v, X_v; X_q; t\right)$, between two consecutive years, and rearranging the terms, allocative efficiency change is obtained as

$$(23)\quad \widehat{\dot{AE}}_{st} = -\widehat{\dot{TE}}_{st} + \left[\ln \hat{C}\left(\underline{Y}_{st}, w_{vst}; X_{qst}; t\right) - \ln \hat{C}\left(\underline{Y}_{st-1}, w_{vst-1}; X_{qst-1}; t-1\right)\right] -$$
$$[\ln C_v(w_{st}, X_{vst}; t) - \ln C_v(w_{st-1}, X_{vst-1}; t-1)].$$

The term $\widehat{\dot{TE}}_{st}$ is recovered from the econometric estimates as $\widehat{\dot{TE}}_{st} \equiv -\left(\hat{\rho}_{1s} + \frac{1}{2}\hat{\rho}_{2s}(2t-1)\right)$. The second term is computed as the solution to the cost-minimization problem (20) for state s in years t and $(t-1)$. Finally, the third term is calculated directly from the observed cost data.

Recovering Technical Change

Since technical change is defined as $TC \equiv -\frac{\partial \ln C\left(\underline{Y}, w_v; X_q; t\right)}{\partial t}$, here it is estimated as

$$(24)\quad \widehat{TC}_{st} = -\left[\ln \hat{C}\left(\underline{Y}_{st}, w_{vst}; X_{qst}; t+1\right) - \ln \hat{C}\left(\underline{Y}_{st}, w_{vst}; X_{qst}; t\right)\right].$$

The minimum costs involved in this expression are computed by solving the cost-minimization problem (20) for state s, keeping variable input prices, quasi-fixed input quantities, and output

[7] Note that $\hat{\tilde{x}}^*_{v_1st} = 0$ because $\tilde{x}_{v_1st} \equiv \ln\left(\frac{X_{v_1st}}{X_{v_1st}}\right) = 0$ by construction.

quantities constant at their year-t levels, while changing the (distance function) time component from t to $(t+1)$.

Recovering Cost Elasticities

The terms MUE, SE, and $QFIE$ in equation (7) require the computation of the cost elasticity with respect to the *n*-th output, $\varepsilon_{CY_n}\left(\underline{Y}, w_v; X_q; t\right) \equiv \frac{\partial \ln C(\underline{Y}, w_v; X_q; t)}{\partial y_n}$, and the cost elasticity with respect to the g-th quasi-fixed input, $\varepsilon_{CX_{q_g}}\left(\underline{Y}, w_v; X_q; t\right) \equiv \frac{\partial \ln C(\underline{Y}, w_v; X_q; t)}{\partial x_{q_g}}$. Since there are no closed-form solutions for these elasticities, they are calculated by means of the following numerical approximations

$$(25)\quad \hat{\varepsilon}_{CY_n}\left(\underline{Y}_{st}; w_{vst}; X_{qst}; t\right) = \frac{\ln \hat{C}\left(1.01\times \underline{Y}_{n,st}; \underline{Y}_{l\neq n,st}; w_{vst}; X_{qst}; t\right) - \ln \hat{C}\left(\underline{Y}_{st}; w_{vst}; X_{qst}; t\right)}{\ln\left(1.01\times \underline{Y}_{n,st}\right) - \ln \underline{Y}_{n,st}}, \text{ and}$$

$$(26)\quad \hat{\varepsilon}_{CX_{q_g}}\left(\underline{Y}_{st}; w_{vst}; X_{qst}; t\right) = \frac{\ln \hat{C}\left(\underline{Y}_{n,st}; w_{vst}; 1.01\times X_{q_g st}; X_{q_h\neq q_g,st}; t\right) - \ln \hat{C}\left(\underline{Y}_{st}; w_{vst}; X_{q_g st}; t\right)}{\ln\left(1.01\times X_{q_g st}\right) - \ln X_{q_g st}},$$

where optimization (20) is used to compute minimum costs.

Estimating Weather Effects

While USDA original production variables are used to estimate Model 1, and the resulting parameter estimates are used to calculate TFP change according to equation (7); weather-filtered variables are used to estimate Model 2, and the resulting parameter estimates are used to calculate the net weather effect on TFP change ($NWEFF$), and the weather-filtered TFP change ($T\dot{FP}^{WF}$) according to equation (8). We create weather-filtered variables using an adaptation of the weather model developed by Ortiz-Bobea, Knippenberg, and Chambers (2018). We use a spline with three equally-spaced knots to model exposure to temperature levels and a quadratic specification to model precipitation. For each variable, we conduct a search grid based on a 10-fold cross-validation over all calendar periods to identify the "optimal" season. This corresponds to the calendar period that provides the best out-of-sample prediction accuracy. Using the optimal season for each variable in each region, we filter out the effect of abnormal weather on output and input quantities and prices by predicting the value of each variable evaluated at normal weather conditions. The weather-filtered variables are used to calculate the corresponding aggregate output and input levels under normal weather conditions, i.e. $\hat{Y}^e \equiv \sum_n \hat{p}_n^e \hat{Y}_n^e / \hat{P}^e$ and $\hat{X}^e \equiv (\sum_i \widehat{w}_{v_i}^e \hat{X}_{v_i}^e + \sum_g \widehat{w}_{q_g}^e \hat{X}_{q_g}^e)/\widehat{W}^e$. The resulting estimates are in turn used to compute the abnormal weather output and input effects, $\hat{\dot{\gamma}}_n = \dot{Y}_n - \hat{\dot{Y}}_n^e$, and $\hat{\dot{\delta}}_j = \dot{X}_j - \hat{\dot{X}}_j^e$, respectively, and $TF\dot{P}^{WF}$.

An alternative approach to incorporating weather effects into our model is to develop an annual index of weather conditions and to treat it as an exogenous and free input of production in the input distance function. Njuki, Bravo-Ureta, and O'Donnell (2018) use growing season temperature and precipitation, and intra-annual standard deviations of temperature and precipitation as exogenous and free inputs of production in a stochastic frontier Cobb-Douglass production model, to find negligible weather effects on TFP change. The two main advantages of our approach over the alternative are the added flexibility gained by letting data dictate what is considered "normal" weather for a particular state-year combination (instead of using a fixed growing season), and the additional information gained by estimating separately weather effects on outputs and inputs (instead of only estimating the aggregate effect on TFP change).

Data

In order to highlight the varying effects of abnormal weather across different regions, we focus on two regions: the Pacific Region (California, Oregon, Washington), and the Central Region (Iowa, Illinois, Indiana, Michigan, Missouri, Minnesota, Ohio, and Wisconsin). This regional grouping has been used by Alston et al. (2010) and overlaps with the old ERS Farm Production Regions (USDA 2000).[8] State-level data for both regions over 1964-2004 is derived from the official USDA panel dataset on

[8] The current ERS Farm Production Regions map (USDA 2000) is based on county-level data, and several states belong to multiple regions. Given that the data used in the current study is aggregated at the state-level, we are not able to use the current ERS regions.

agricultural production for the United States (USDA 2017, table 23), which is described in Ball, Hallahan, and Nehring (2004). It contains N = 3 aggregate agricultural outputs (crops, livestock, and other farm outputs), and $I + G$ = 4 inputs (capital, labor, materials, and land) for each of the states. All quantities are measured as transitive implicit Fisher quantity indexes, calculated with price indexes with bases equal to unity in Alabama in 1996. The transitivity of the quantity indexes ensures that they are comparable across states and years. Summary statistics for the original production data are reported in Table 1.

The crop output, $H \equiv Y_1$, measures the aggregate production of grains, oilseeds, cotton, and tobacco. The livestock output, $V \equiv Y_2$, is the aggregate production of livestock, dairy, poultry, and eggs. The other farm output, $O \equiv Y_3$, measures the aggregate production of fruits, vegetables, nuts, and other miscellaneous outputs. The output quantity for each crop and livestock category consists of quantities of commodities sold off the farm, additions to inventory, and quantities consumed as part of final demand in farm households during the calendar year. Off-farm sales are defined in terms of output leaving the sector within the state, and sales to the farm sector in other states.

Materials, $M \equiv X_{v_1}$, is the numeraire (variable) input used in this analysis, and it includes fertilizers, pesticides, energy and other miscellaneous inputs. Capital, $K \equiv X_{v_2}$, represents the service flows of durable equipment, and stocks of inventories. Labor, $L \equiv X_{v_3}$, is the quality-adjusted amount of hired and self-employed labor. Finally, land, $A \equiv X_{q_1}$, measures the service flows of real estate inventories. The present analysis assumes that materials, capital, and labor are variable inputs, and land is a quasi-fixed factor, i.e. $X_v = \{M, K, L\}$ and $X_q = \{A\}$.

Climate data is obtained from two sources. Monthly precipitation is obtained from the PRISM Climate Group at Oregon State University, whereas minimum and maximum daily temperatures are obtained from Schlenker and Roberts (2009). Both of these datasets have a spatial resolution of 4 km for the continental United States. We fit a double sine curve through the daily minimum and maximum temperature points to derive monthly measures of time exposure to each 1°C temperature bin between –15 and 50°C over the 1964-2004 sample period. We spatially aggregate monthly precipitation and temperature exposures to the state level by weighting the fine-scale grid cells based on their cropland area, as measured by USDA's Cropland Data Layer.

Econometric Estimation Method

We use Bayesian methods to estimate the system of equations (10)-(19). Bayesian techniques are quite advantageous for the present study, because they greatly facilitate imposing the desired monotonicity and concavity restrictions in estimation ((13)-(15) and (16)-(17), respectively), and performing the corresponding inferences (e.g., O'Donnell and Coelli (2005) and Lence and Plastina (2018, 2019)). It would be quite difficult, if not impossible, to impose restrictions (13)-(17) using classical methods. Further, sampling theory inference under inequality constraints may be problematic (O'Donnell, Shumway, and Ball 1999).

An additional advantage of the Bayesian approach is that it generates full posterior distributions for the estimated parameters from the distance function, as well as functions of such parameters. This property is particularly important here, because we are interested in the individual components of TPF change (8), which are highly nonlinear functions of the estimated parameters. The Bayesian approach allows us to compute the full posteriors in a straightforward manner, which is useful because approximations like the delta method need not fare well when dealing with functions of parameters that may exhibit skewed posteriors (as when parameters are subject to restrictions, which is the case here)). The Bayesian methods also enable us to ensure that all points on the posterior pdfs satisfy the restrictions imposed in estimation.[9]

[9] It is generally not possible to ensure that such restrictions be satisfied over the entire confidence intervals computed by means of approximations like the delta method.

For all models, estimation is conditioned on the initial set of observations (i.e., the initial condition consists of the observed values in the year 1960). Proper posteriors are guaranteed by adopting weakly informative proper priors for all of the estimated parameters, following the typical parameterizations reported in *Stan User's Guide* (Stan Development Team 2019) and the recommendations by Gelman (https://github.com/stan-dev/stan/wiki/Prior-Choice-Recommendations). In the case of the unrestricted coefficients $\{\alpha, \beta, \zeta, \varphi, \varsigma\}$ of the system of equations (10)-(18)-(19), the priors are Student-*t*[3, 0, max(5, >15×PostStDev$_i$)], i.e., Student's *t* distributions with 3 degrees of freedom, 0 location equal to zero, and scale of max(5, >15×PostStDev$_i$), where >15×PostStDev$_i$ is a scalar sufficiently large to ensure that parameter *i*'s prior standard deviation is at least 15 times as large as its posterior standard deviation.[10] The covariance matrix of residuals ϑ_{st}, $\vartheta_{st}^{v_j}$, and $\vartheta_{st}^{q_h}$ is computed as the product

$$(27)\quad \begin{bmatrix} \sigma_{\vartheta}^2 & \sigma_{\vartheta\vartheta^{v_2}} & \sigma_{\vartheta\vartheta^{v_3}} & \sigma_{\vartheta\vartheta^{q_1}} \\ \sigma_{\vartheta\vartheta^{v_2}} & \sigma_{\vartheta^{v_2}}^2 & \sigma_{\vartheta^{v_2}\vartheta^{v_3}} & \sigma_{\vartheta^{v_2}\vartheta^{q_1}} \\ \sigma_{\vartheta\vartheta^{v_3}} & \sigma_{\vartheta^{v_2}\vartheta^{v_3}} & \sigma_{\vartheta^{v_3}}^2 & \sigma_{\vartheta^{v_3}\vartheta^{q_1}} \\ \sigma_{\vartheta\vartheta^{q_1}} & \sigma_{\vartheta^{v_2}\vartheta^{q_1}} & \sigma_{\vartheta^{v_3}\vartheta^{q_1}} & \sigma_{\vartheta^{q_1}}^2 \end{bmatrix} = \sigma\Lambda\Lambda^{\mathrm{T}}\sigma^{\mathrm{T}},$$

where σ is a diagonal matrix, Λ is the Cholesky factor of the correlation matrix, and superscript "T" denotes the transpose (i.e., the correlation matrix can be obtained as the product $\Lambda\Lambda^{\mathrm{T}}$). The priors for matrix σ's parameters $\{\sigma_{\vartheta}, \sigma_{\vartheta^{v_2}}, \sigma_{\vartheta^{v_3}}, \sigma_{\vartheta^{q_1}}\}$ are Cauchy(0, 2.5), whereas the prior for matrix Λ is a Cholesky LKJ Correlation Distribution with shape parameter 1 (Lewandowski, Kurowicka, and Joe 2009). The proposed prior for the Cholesky factor matrix guarantees that the product ($\Lambda\Lambda^{\mathrm{T}}$) is a positive definite correlation matrix.

To impose convexity in outputs, the symmetric matrix of α_{mn} coefficients (15) is estimated similarly to the covariance matrix (27). That is, we estimate it as the product

[10] The prior Student's *t* distribution and its proposed parameterization are based on Gelman's recommendations. He argues that the Normal distribution is not a robust prior and therefore not recommended as weakly informative. He also states that a prior standard deviation smaller than 10 times the posterior standard deviation is informative.

$$(28)\quad \begin{bmatrix} \alpha_{HH} & \alpha_{HV} & \alpha_{HO} \\ \alpha_{HO} & \alpha_{VV} & \alpha_{VO} \\ \alpha_{HO} & \alpha_{VO} & \alpha_{OO} \end{bmatrix} = \Phi \Upsilon \Upsilon^{\mathrm{T}} \Phi^{\mathrm{T}},$$

where Φ is a (3 × 3) diagonal matrix, and Υ is the Cholesky factor of a (3 × 3) correlation matrix. The priors for the parameters in matrix Φ's diagonal are Student-t[3, 0, max(5, >15×PostStDev$_i$)], whereas the prior for the matrix Υ consists of a Cholesky LKJ Correlation Distribution with shape parameter 1 (Lewandowski, Kurowicka, and Joe 2009). This prior for the Cholesky factor matrix ensures that expression (28) yields a positive definite matrix (and therefore convexity).

Concavity in variable inputs is imposed in an analogous manner, by estimating the symmetric matrix of $\beta_{v_i v_j}$ coefficients (17) as if it were the negative of a covariance matrix. Note, however, that only coefficients $\{\beta_{KK}, \beta_{KL}, \beta_{LL}\}$ are estimated directly, because β_{MM}, β_{KM}, and β_{LM} are calculated from the former by imposing the homogeneity condition (12). Therefore, the symmetric matrix with coefficients $\{\beta_{KK}, \beta_{KL}, \beta_{LL}\}$ is first computed as the negative of a covariance matrix.[11] Then, the full symmetric matrix (16) is computed post-estimation, and all Monte Carlo draws for which the full matrix fails the concavity condition are discarded to ensure that coefficients $\{\beta_{KK}, \beta_{KL}, \beta_{LL}, \beta_{MM}, \beta_{KM}, \beta_{LM}\}$ satisfy the desired restriction. In other words, concavity is not fully imposed in estimation, but enforced ex post.

The condition that the distance function be non-increasing in outputs (13) is imposed by estimating the α_n coefficients in regression (10) as

$$(29)\quad \alpha_n = -\psi_n^2 - \max_{s,t}\left[\textstyle\sum_{m\in\{H,V,O\}} \alpha_{mn}\, y_{mst} + \sum_{j\in\{K,L,A\}} \delta_{nj}\, \tilde{x}_{jst} + \lambda_t \alpha_{n\Theta}\right],$$

for $n \in \{H, V, O\}$, with Student-t[3, 0, max(5, >15×PostStDev$_i$)] priors for parameters ψ_H, ψ_V, and ψ_O.

The method used to impose conditions (14)-(15), i.e., that the distance function be non-decreasing in inputs, is analogous to the one underlying expression (29), so that

$$(30)\quad \beta_{v_j} = \psi_{v_j}^2 - \min_{s,t}\left[\textstyle\sum_{i\in\{K,L\}} \beta_{v_i v_j}\, \tilde{x}_{v_i st} + \beta_{v_j A} x_{Ast} + \sum_{m\in\{H,V,O\}} \delta_{n v_j}\, y_{nst} + \lambda_t \beta_{v_j \Theta}\right], j \in \{K, L\},$$

[11] Since in this instance only a single correlation coefficient is being estimated, we use a Uniform(-1, 1) prior for it instead of a Cholesky LKJ Correlation Distribution.

(31) $\beta_A = \psi_A^2 - \min_{s,t}\left[\sum_{i\in\{K,L\}} \beta_{iA}\, \tilde{x}_{v_i st} + \beta_{AA} x_{Ast} + \sum_{m\in\{H,V,O\}} \delta_{nA}\, y_{nst} + \lambda_t \beta_{A\Theta}\right]$,

with Student-*t*[3, 0, max(5, >15×PostStDev$_i$)] priors for parameters ψ_K, ψ_L, and ψ_A. But due to the fact that the coefficient for the materials input β_M is recovered after estimation from the homogeneity constraint (11) (i.e., $\beta_M = 1 - \beta_K - \beta_L$) rather than estimated directly, condition (14) for the materials input M is enforced ex post, by dropping any Monte Carlo draw that does not meet it.

The Bayesian estimation is performed by means of RStan (https://cran.r-project.org/web/packages/rstan/vignettes/rstan.html), the R interface to Stan, in the R version 3.5.1 programming language and software environment (https://www.r-project.org). Hamiltonian Monte Carlo sampling with the No-U-Turn sampler (Stan Development Team 2019) is implemented using Stan 2.18.2. Each model is estimated using four Hamiltonian Monte Carlo chains, with 10,000 iterations per chain. The first 2,500 iterations of each chain are discarded as a burn-in period. The Gelman and Rubin (1992) test is then applied to check the convergence of the remaining part of the chains for each of the parameters. The Gelman and Rubin test checks the convergence of a parameter's Markov chain to its posterior distribution, i.e., whether the parameter estimates are stationary, by comparing the variances of both within the chains and between the chains. The Gelman-Rubin test statistics are smaller than 1.01 for all parameters in all of the estimated models, providing strong evidence of convergence. Upon convergence, and after discarding the draws that do not meet the homogeneity condition for the materials input and the concavity restriction, 5,000 of the remaining simulated values for each parameter are taken to be draws from the parameter's posterior marginal distribution. The 5,000 sets of simulated parameters are also used to obtain the posterior distributions for the desired functions of paramaters.

Results and Discussion

For simplicity of exposition, we first focus on the estimated effects of abnormal weather on TFP change and on the profitability of the farm sector in each state of the Central and Pacific regions over

1964-2004. Then, we comment on the estimated components of weather-filtered TFP change from Model 2, and compare them with the results from Model 1 based on original production data (i.e., ignoring weather effects). Direct comparison of the average estimated effects of each of the nine components of TFP change derived from Models 1 and 2, allows us to measure the biases in their estimated contributions to productivity growth when weather effects are not accounted for. This is the first study to measures those biases in U.S. agriculture.

Estimated Effects of Abnormal Weather

Table 2 provides information about the models we selected to filter out abnormal weather conditions from price and quantity variables. The table shows, for each variable and region, the extent of the optimal season (i.e., the start and end of the calendar period providing the best out-of-sample prediction accuracy), the reduction in out-of-sample MSE relative to a model without weather variables, and the correlation of the observed level of the variable and the fitted values of the model. For instance, we find that weather conditions are able to best predict crop quantity in the Central Region when the season is confined to April-September, which roughly coincides with the usual growing season in that region. For that variable, our model reduces out-of-sample MSE by 46% relative to a model without weather variables. In other words, our weather variables explain about half of the variation in crop quantity around the trend. The correlation between the observed and fitted values are very close to 1, suggesting that our weather-filtration exercise is mostly removing the effects of abnormal weather conditions, and not introducing noise to variable levels.

Table 3 suggests that even though abnormal weather effects have, by construction, relatively small mean net effects on TFP change (ranging from -0.1960 percentage points for Minnesota to 0.2747 percentage points for Illinois), they can have major impacts on TFP change on any given year (ranging from -23.36 percentage points for Missouri in 1980, to 22.09 percentage points for Illinois in 1989). Mean weather effects on output change ($\hat{\gamma}$) were larger in absolute values than mean weather effects on input change ($\hat{\hat{\delta}}$) for all states in the sample except for Minnesota, where both effects are close in absolute value.[12] Illinois, Indiana, Michigan, and Ohio experienced, on average, productivity-enhancing abnormal weather effects through both realized output levels higher than expected under normal weather conditions, and realized input use levels lower than expected under normal weather conditions. In the case of California, Iowa, and Missouri, on average the productivity-enhancing abnormal weather effects on outputs dominated the productivity-reducing weather effects on inputs. In contrast, for Oregon, Washington, and Wisconsin, on average the productivity-reducing weather effects on outputs dominated the productivity-enhancing abnormal weather effects on inputs. Finally, Minnesota experienced productivity-reducing abnormal weather effects on both outputs and inputs.

On average, the net weather effect on TFP change ($N\widehat{WEF}F = \hat{\gamma} - \hat{\hat{\delta}}$) in the Pacific region was -0.0369 percentage points, compared to 0.1135 percentage points in the Central Region. Overall, weather plays a larger role explaining output changes than input changes, and plays a greater role in explaining both output and input changes in the Central Region than in the Pacific Region. These findings are largely in line with Ortiz-Bobea, Knippenberg, and Chambers (2018), who find that weather primarily affects TFP through output in the Eastern half of the country; and with Njuki, Bravo-Ureta, and O'Donnell (2018) who find that climatic effects slowed down annual TFP growth across the 48 continental states of the United States by an average -0.012 percentage points over 1960-2004.

The average annual monetary value of abnormal weather effects on revenues, $P(Y - Y^e)$, was negative for the states in the Pacific region ($5.9 million (Alabama 1996=1)), and positive for the states in the Central Region ($16.7 million (Alabama 1996=1)) over 1964-2004 (Table 4). However, the means hide substantial variability in annual impacts. In terms of the annual monetary value of

[12] However, the coefficients of variation of weather effects on input changes ($\hat{\hat{\delta}}$) were consistently larger in absolute value than the coefficients of variation of the weather effects on output changes ($\hat{\gamma}$) for all states.

abnormal weather on costs of production, $W(X - X^e)$, on average it had a cost-reducing effect in the Pacific states ($9.4 million (Alabama 1996=1)) and a cost-increasing effect in the Central states ($2.8 million (Alabama 1996=1)) over 1964-2004. Except for Oregon, Washington, and Missouri, all states in the sample benefited over the long term from unexpected weather shocks, as indicated by the positive weather effects on profitability, IAW.

Since all price indexes in the USDA database are expressed in terms of their values with respect to Alabama in 1996, calculating the ratios of monetary values of abnormal weather effects to profits (expressed in deviations of profits in Alabama 1996) is meaningless. Instead, we inquire whether the weather effects were consistent in mean values and dispersion across the first and second half of the sample (Table 5). The only statistically significant differences in means on revenues and profitability (according to one-way ANOVA F-tests at the 5% level of confidence) are observed for Minnesota, where weather effects switched from negative to positive. However, variance equality of net weather effects on profitability across periods was rejected (according to Fligner-Killeen Chi-square tests at the 10% level of confidence) for all states in the sample but Michigan, Minnesota, and Wisconsin. Our findings that the variability of net weather effects on profitability has increased from 1964-1984 to 1985-2005 is in line with Ortiz-Bobea, Knippenberg, and Chambers (2018).

Parameter Estimates from the Distance Function

Tables 6a and 6b show two sets of selected parameter estimates each, based on equations (10)-(19) for the Pacific and the Central region, respectively: Model 1 is estimated using the original production variables from USDA, whereas Model 2 is estimated using only the weather-filtered variables. Note that while the structures are similar across models, the variables used in estimation are different, and therefore parameter estimates are not directly comparable. The descriptive statistics of the 5,000 sets of parameter estimates include the mean, median, standard deviation and 95% credible intervals (CIs). In both models for both regions, the estimated cross-equation correlations between ϑ_{st} and ϑ_{st}^{K} are positive and significant (their corresponding 95% CIs exclude the null value), suggesting that the system-of-equations approach followed in this study is superior to the alternative single-equation approach.

Scale Effect, $\widehat{SE}$

All states have benefited from changing their scale of production (Table 7). The estimated annual contribution of the scale effect to weather-filtered TFP change from Model 2 averaged 1.51% in the Pacific Region, and 0.50% in the Central Region. However, annual estimates varied substantially, ranging from -11.21% (Iowa, 2003) to 11.55% (Minnesota, 1994). Comparing the estimated scale effects from Model 2 versus the corresponding estimates from Model 1, it becomes apparent that failing to account for weather effects induces substantial biases in the estimated scale effects: -0.71 percentage points for the Pacific Region, and 0.53 percentage points for the Central Region, on average.

Mark Up Effect, $\widehat{MUE}$

As it was expected from a highly competitive farm sector, the mark up effect made a negligible average contribution to weather-filtered TFP change (-0.07%) across all states in the sample (Model 2 in Table 8). Only Illinois benefited substantially from non-marginal pricing, adding an average 0.66% to weather-filtered TFP change over 1964-2004. Wisconsin, Minnesota, Washington, and Oregon saw their weather-filtered TFP change reduced, on average, by more than 0.3% annually over the same period due to negative markup effects. It is important to note that the bias introduced by failing to account for weather effects (Model 1 in Table 8) is substantial: 0.84 percentage points in the Pacific Region, and -0.49 percentage points in the Central Region, on average.

Adjusted Technical Change, $\frac{C_v(w_v,X_v)}{C_o(w,X)}\widehat{TC}$

Estimates of annual adjusted technical change are summarized in Table 9. As expected, $\frac{C_v(w_v,X_v)}{C_o(w,X)}\widehat{TC}$ values are consistent across states in the same region, reflecting the fact that technical change measures the change in the frontier input distance function, irrespective of the location of the input distance functions for states outside the frontier. It is apparent from Table 9 that weather-adjusted technical change (Model 2) in the Pacific region has been stronger than in the Central region over 1964-2004: 0.67% versus -0.04%, on average. Failing to account for weather effects induces huge upward biases in the estimates of adjusted technical change for the Pacific Region (averaging 1.10 percentage points), and smaller downward biases for the Central Region (averaging -0.13 percent points).

Figure 1 illustrates the evolution of adjusted technical change for California and Iowa, the top two agricultural producers in the sample (accounting, respectively, for 9.8% and 7.1% of the total value of agricultural production in the 48 contiguous states of the United States over the sample period). Several observations can be made from Figure 1. First, adjusted technical change is more volatile in California than in Iowa. Second, the average estimate of adjusted technical change in California using the original variables in Model 1 is strongly affected by the annual estimates in 2001 and 2004. Using the weather-filtered variables in Model 2, the estimated average contribution of technical change to TFP change drops by about two-thirds.

Our regional estimates of adjusted technical change do not conform to the temporal patterns of the national estimates of technical change described by Plastina and Lence (2018), who found "a clear slowdown" in the rates of technical change, and sustained technical regress in 1981-1992. Given that the underlying methodology is similar to that of Plastina and Lence (2018), and that the same database was used for both studies, the difference in results highlights the importance of measuring technical change by productive regions with similar production profiles rather than across multiple states with widely different production systems.

Finally, it must be noted that technical change in our methodological framework is strictly defined as the reduction in minimum costs stemming only from the change in the annual dummy variable d_t and its corresponding coefficient λ_t in the flexible index of technical change $\sum_{t=1}^{T} \lambda_t d_t$, keeping everything else constant. The other TFP component in our model derived only as a function of time is adjusted technical efficiency change, discussed next.

Adjusted Technical Efficiency Change, $\frac{C_v(w_v, X_v)}{C_o(w, X)} \widehat{\dot{TE}}$

Estimates of changes in adjusted technical efficiency are summarized in Table 10. The average annual median estimate across all states and years in Model 2 is 0.75%, with median annual estimates ranging from -1.36% (Missouri, 1964) to 3.23% (Indiana, 2004). All states in the Central region show positive and high average rates of adjusted technical efficiency change, indicating that their agricultural production systems have successfully managed to proportionally reduce the systematic overuse of all variable inputs and get closer to the contemporaneous minimum cost frontier over the period 1964-2004. Among the Pacific region states, only Oregon shows positive average rate of adjusted technical efficiency change over the sample period, but all states in the region experienced very small changes (in absolute value) in technical efficiency. Failing to account for weather effects (Model 1), results in inflated rates of technical efficiency for all states in the Central region but Michigan, and deflated rates for all states in the Pacific region, with biases averaging 0.17% and -0.38%, respectively.

Adjusted Allocative Efficiency Change, $\frac{C_v(w_v, X_v)}{C_o(w, X)} \widehat{\dot{AE}}$

Estimates of changes in adjusted allocative efficiency are summarized in Table 11. The average annual median estimate across all states and years is -0.30% in Model 2, but the ranges of median annual estimates are quite wide, going from -19.60% (Wisconsin, 1998) to 10.11% (Missouri, 1980). All states but Oregon show negative average median adjusted allocative efficiency changes in Model 2, suggesting that the gap between shadow and market prices faced by farms increased through time, or that it became increasingly costly to adjust production practices to annual changes in the relative prices capital, labor, and materials. However, adding up the estimated adjusted technical and allocative efficiency changes for each state, the resulting changes in the overall cost efficiency, as defined in (3), have been positive, on average, for all states except for California and Washington. The corollary of this analysis is that through time, the gap between minimum variable cost and observed variable cost has shrunk in most states in the sample.

The biases induced by failing to account for weather effects on the estimation of adjusted allocative efficiency changes in Model 1 average -0.57% and -0.04% for the Pacific and the Central region, respectively.

Quasi-Fixed Input Effect, $\widehat{QFIE}$

The average annual impact of land quasi-fixity on weather-filtered TFP change (i.e., $-\widehat{QFIE}$) is negligible for all states but Michigan (-0.15%), averaging 0.02% and -0.06% for the Pacific and Central regions, respectively (Model 2 in Table 12). While the bias induced by failing to account for weather effects in the estimation of $-\widehat{QFIE}$ is very small for the Central region, it is substantial for the Pacific region, averaging -0.04% and -0.22%, respectively.

Input Price Factor, $\widehat{IPF}$

The average annual impact of the input price factor on weather-filtered TFP change (i.e., $-\widehat{IPF}$) is positive for all states but Michigan (-0.15%) and Missouri (-0.13%), averaging 0.18% and 0.12% for the Pacific and Central regions, respectively (Model 2 in Table 13). The states that benefited the most from changes in observed input prices were Minnesota and Oregon, where weather-filtered TFP change increased by an average 0.37% and 0.24%, respectively, due to $-\widehat{IPF}$. For all states but Michigan, the bias induced by failing to account for weather effect on $-\widehat{IPF}$ is negligible, averaging 0.05% and 0.04% in the Pacific and Central regions, respectively.

Output and Input Price Aggregation Effects, $\widehat{OPAE}$ & $-\widehat{IPAE}$

Estimates of the output and (the negative of) input price aggregation effects, $\widehat{OPAE}$ and $-\widehat{IPAE}$, are summarized in Tables 14 and 15, respectively. The average annual median $\widehat{OPAE}$ across all states and years is 0.002% on the weather-filtered variables (Model 2 in Table 14). The average annual contribution of the input price aggregation effect to weather-filtered TFP change, i.e. $-\widehat{IPAE}$, amounted to 0.33% (Model 2 in Table 15). The combination of these two effects on weather-filtered TFP change is non-negligible for all states in the sample, averaging 0.42% in the Central region and 0.24% in California and Oregon, and -0.15% in Washington. The biases induced in the estimated output and input price aggregation effects by failing to account for weather effects (Model 1 in Tables 14 and 15) are small in absolute value for most states, except Iowa, Missouri, Minnesota, and Oregon, where the biases in the combined average effects amount to at least 0.10%.

Estimates of TFP Change, $\widehat{T\dot{F}P}$

Our estimates of TFP change based on the original USDA production data and our weather-filtered variables are obtained by simple addition of the estimated components described in equations (7) and (8) derived from Models 1 and 2, respectively. Descriptive statistics for our TFP change estimates, vis-à-vis the official USDA estimates are reported in Table 16. Not only the average annual values of our $\widehat{T\dot{F}P}$ are very close to USDA's (the average difference being 0.15 percentage points in Model 1 and 0.08 percentage points in Model 2), but the correlations between our series and USDA's are notably high (Figure 2): the Pearson correlation coefficients between $\widehat{T\dot{F}P}$ from Model 1 and USDA's $T\dot{F}P$ for the Pacific and the Central regions are 0.991 and 0.996, respectively; while the Pearson correlation coefficients between $\widehat{T\dot{F}P}$ from Model 2 and USDA's $T\dot{F}P$ for the Pacific and the Central regions are 0.995 and 0.998, respectively. Figure 3 illustrates the high degree of overlap between our annual estimates of $\widehat{T\dot{F}P}$ and USDA's $T\dot{F}P$ for California, Iowa, and Illinois. Taking into account the average differences between USDA's and our estimates of TFP change, along with the correlation coefficients, it is evident that Model 2 provides a better fit to the TFP data than Model 1.

From observation of Tables 3, 7-16, it is apparent that failing to account for weather effects results in substantial biases in the estimated relative contributions of some of the components of TFP change to productivity growth. Figure 3 illustrates those biases for California, Iowa, and Illinois.

By direct comparison of USDA's $T\dot{F}P$ and the weather-filtered TFP change estimated from Model 2, $\widehat{T\dot{F}P}^{WF}$, it becomes evident that agricultural productivity growth explained by factors other than weather was much slower than estimated in previous studies. The average difference between $\widehat{T\dot{F}P}^{WF}$ and USDA's $T\dot{F}P$ amounts to -0.20 percentage points among the states of the Central region plus California, suggesting that agricultural productivity growth due to factors other than weather was about 11% lower than estimated by the USDA in those states over 1964-2004. This finding calls to question previous estimates on the cost-effectiveness and rates of return to public policies based on non-weather filtered productivity estimates (e.g., everything else constant, the rates of return to public investments in productivity-enhancing policies will be smaller when calculated based on $\widehat{T\dot{F}P}^{WF}$ than when calculated based on USDA's $T\dot{F}P$). This is the first study to provide a counterfactual analysis of the biases induced in TFP change estimates by failing to account for weather effects.

Concluding comments

This study develops a novel analytical framework to estimate agricultural TFP change in the presence of quasi-fixed inputs of production and abnormal weather effects, and to estimate monetary impacts of weather effects on agricultural production. The underlying technology is represented by a flexible input distance function estimated using cutting-edge Bayesian methods. Using agricultural production data for the Pacific and Central regions of the U.S., TFP change is estimated as the direct sum of its components: net weather effects, technical change, changes in technical and allocative efficiency, a markup effect, a scale effect, an input price factor, an output price aggregation effect, and an input price aggregation effect. We find substantial weather effects on TFP change, in particular in the Central region. Our estimates of TFP change are not only very highly correlated with changes in USDA's TFP indexes by state, but they also show a prominent overlap in terms of direction and magnitude of changes for all states. By comparing the results from the weather-filtered model with the results from a model estimated on the original production variables, we provide estimates of the biases induced in each of the estimated components of TFP change and, consequently, on the level of TFP change explained by non-weather-related factors. This is the first study to present estimates of those biases based on a counterfactual analysis.

This study provides the basis for addressing more detailed questions about the drivers of each of the components of TFP change by state. In particular, previous evaluations of public policies to enhance agricultural productivity are called into question when the weather-filtered TFP change was about 11% slower than the TFP change calculated from USDA's indexes over 1964-2004 for states in the Central region and California.

Several caveats apply to the present study, including that its focus is on overall input efficiency, and an alternative focus on output efficiency might yield different results; and as with any stochastic frontier approach, the advantage of being able to distinguish noise from inefficiency comes at the cost of being unable to distinguish inefficiency from the effects of using inappropriate functional forms.

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Table 1. Descriptive Statistics of the Original Variables

Variable	Unit	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
Pacific Region						
Aggregate Output quantity	thousand $ 1996	8,653,085	8,650,357	1,423,835	31,595,500	135
Aggregate Output price index	1 for AL 1996	0.728	0.263	0.311	1.159	135
Crops quantity	thousand $ 1996	5,342,744	5,337,050	695,823	19,386,468	135
Crops price index	1 for AL 1996	0.755	0.273	0.325	1.250	135
Livestock quantity	thousand $ 1996	2,413,995	2,348,234	560,152	8,497,604	135
Livestock price index	1 for AL 1996	0.759	0.273	0.329	1.330	135
Other Outputs quantity	thousand $ 1996	588,691	656,787	92,939	2,660,367	135
Other Outputs price index	1 for AL 1996	0.734	0.407	0.160	1.542	135
Aggregate Input quantity	thousand $ 1996	7,354,162	5,538,987	2,534,379	19,814,710	135
Aggregate Input price index	1 for AL 1996	0.702	0.385	0.152	1.375	135
Capital quantity	thousand $ 1996	764,329	382,123	372,157	1,617,403	135
Capital price index	1 for AL 1996	0.643	0.375	0.153	1.223	135
Labor quantity	thousand $ 1996	3,458,452	2,476,843	1,147,496	9,090,775	135
Labor price index	1 for AL 1996	0.439	0.288	0.086	1.136	135
Land quantity	thousand $ 1996	954,959	697,506	383,826	2,263,359	135
Land price index	1 for AL 1996	0.703	0.551	0.017	1.748	135
Materials quantity	thousand $ 1996	2,849,246	2,536,910	707,862	9,451,845	135
Materials price index	1 for AL 1996	0.919	0.430	0.294	1.628	135
Central Region						
Aggregate Output quantity	thousand $ 1996	7,172,304	3,064,925	2,819,310	17,576,098	360
Aggregate Output price index	1 for AL 1996	0.730	0.234	0.280	1.067	360
Crops quantity	thousand $ 1996	3,842,448	2,002,747	1,370,176	10,315,345	360
Crops price index	1 for AL 1996	0.755	0.232	0.320	1.215	360
Livestock quantity	thousand $ 1996	3,148,038	1,538,868	1,219,760	7,234,754	360
Livestock price index	1 for AL 1996	0.710	0.257	0.238	1.249	360
Other Outputs quantity	thousand $ 1996	200,857	82,840	65,047	648,510	360
Other Outputs price index	1 for AL 1996	0.738	0.395	0.186	1.466	360
Aggregate Input quantity	thousand $ 1996	8,989,993	2,868,907	4,661,367	17,541,620	360
Aggregate Input price index	1 for AL 1996	0.697	0.374	0.149	1.460	360
Capital quantity	thousand $ 1996	1,536,370	549,372	697,691	3,330,621	360
Capital price index	1 for AL 1996	0.637	0.368	0.143	1.200	360
Labor quantity	thousand $ 1996	3,893,924	1,590,993	1,465,795	8,382,092	360
Labor price index	1 for AL 1996	0.495	0.403	0.062	2.004	360
Land quantity	thousand $ 1996	868,524	244,391	457,634	1,296,106	360
Land price index	1 for AL 1996	0.697	0.556	0.014	2.076	360
Materials quantity	thousand $ 1996	3,413,585	1,406,234	1,495,437	7,694,234	360
Materials price index	1 for AL 1996	0.854	0.347	0.294	1.484	360

Table 2. Best fitting model for each variable by region.

	Pacific Region				Central Region			
	Start of the season (month)	End of the Season (month)	MSE Reduction (%)	Correlation b/Observed and Model Estimate for all states in region	Start of the season (month)	End of the Season (month)	MSE Reduction (%)	Correlation b/Observed and Model Estimate for all states in region
Aggregate Output price index	March	October	4	0.993	February	July	9	0.986
Crops quantity	February	April	12	0.999	April	September	46	0.989
Crops price index	May	August	0	0.988	April	July	13	0.970
Livestock quantity	August	August	1	1.000	March	March	5	0.999
Livestock price index	January	February	3	0.990	April	April	-1	0.986
Other Outputs quantity	January	May	12	0.996	September	September	3	0.980
Other Outputs price index	February	March	4	0.997	May	July	8	0.998
Aggregate Input price index	October	October	12	0.998	July	July	7	0.995
Capital quantity	February	February	5	1.000	January	June	6	1.000
Capital price index	July	October	10	0.999	October	November	3	0.999
Labor quantity	May	June	7	0.996	February	March	1	0.994
Labor price index	February	June	7	0.992	January	February	2	0.982
Land quantity	June	December	12	1.000	September	September	6	1.000
Land price index	September	December	6	0.992	October	November	-1	0.992
Materials quantity	April	July	-3	0.999	March	March	1	0.997
Materials price index	October	October	2	0.996	May	September	13	0.991

Note: MSE = mean square error

Table 3. Estimated Weather Effects, 1964-2004 (in percentage points)

		Weather effect on output change, $\hat{\gamma}$				Weather effect on input change, $\hat{\hat{\delta}}$				Net weather effect on TFP change, $\widehat{NEWFF} = \hat{\gamma}$-$\hat{\hat{\delta}}$			
	N	Mean	StDev	Min	Max	Mean	StDev	Min	Max	Mean	StDev	Min	Max
Pacific Region													
CA	41	0.1532	3.19	-5.30	7.24	0.0489	1.24	-2.56	3.25	0.1043	3.35	-4.65	7.00
OR	41	-0.1273	4.26	-8.69	7.46	-0.0033	1.40	-4.26	3.23	-0.1241	4.14	-8.32	7.65
WA	41	-0.1176	4.66	-9.14	11.23	-0.0265	1.47	-3.98	3.02	-0.0911	4.49	-8.93	10.42
Central Region													
IA	41	0.0521	6.27	-15.82	17.71	0.0173	3.71	-8.66	7.39	0.0348	6.10	-10.68	12.12
IL	41	0.2320	9.20	-24.52	22.45	-0.0427	3.35	-6.88	6.66	0.2747	9.32	-22.48	22.09
IN	41	0.1853	6.49	-18.86	12.62	-0.0809	2.93	-6.59	5.91	0.2662	7.45	-20.36	12.20
MI	41	0.1257	3.38	-8.35	10.70	-0.0539	3.02	-8.73	4.10	0.1796	5.09	-11.48	13.10
MN	41	-0.0980	4.18	-8.25	15.09	0.0980	4.23	-7.02	8.97	-0.1960	5.26	-10.66	14.99
MO	41	0.2094	10.04	-25.57	20.32	0.0488	3.91	-9.62	9.30	0.1606	10.10	-23.36	18.13
OH	41	0.1474	4.81	-12.68	11.61	-0.0727	3.19	-6.46	6.46	0.2201	6.46	-17.06	12.91
WI	41	-0.0345	2.89	-7.16	6.72	-0.0022	3.64	-10.56	7.15	-0.0323	4.67	-10.65	13.17

Table 4. Monetary Value of Abnormal Weather on Revenues, Costs, and Profitability of the Farm Sector, 1964-2004 (in thousands 1996 dollars)

		Weather effect on Revenues $P(Y-Y^e)$				Weather effect on Costs $W(X-X^e)$				Weather effect on Profitability of the Farm Sector IAW			
	N	Mean	StDev	Min	Max	Mean	StDev	Min	Max	Mean	StDev	Min	Max
Pacific Region													
CA	41	-13,426	316,392	-1,025,660	970,445	-24,708	141,195	-429,238	321,367	11,282	376,899	-1,347,027	1,106,742
OR	41	-2,271	23,893	-75,664	37,787	-1,791	20,077	-69,117	47,433	-479	27,210	-109,438	49,566
WA	41	-2,001	37,248	-118,419	75,552	-1,842	30,975	-111,732	69,357	-159	33,388	-76,015	86,867
Central Region													
IA	41	36,757	501,025	-1,253,529	1,322,216	7,191	73,410	-123,081	216,797	29,566	481,141	-1,292,007	1,247,103
IL	41	26,738	589,416	-1,886,551	1,469,963	2,867	36,760	-63,225	82,599	23,872	578,904	-1,868,884	1,434,276
IN	41	7,421	240,450	-730,528	653,497	1,320	22,501	-50,520	54,060	6,101	234,039	-720,716	636,789
MI	41	4,041	101,867	-417,091	237,040	862	21,443	-48,521	77,168	3,179	98,818	-416,725	213,292
MN	41	38,087	254,135	-695,384	596,138	5,147	61,537	-121,072	195,292	32,941	238,124	-689,508	617,515
MO	41	143	326,872	-1,166,240	812,319	950	26,914	-72,633	60,689	-807	319,721	-1,127,947	777,338
OH	41	5,498	177,841	-653,218	390,164	-807	22,696	-48,865	51,952	6,305	175,142	-649,160	383,063
WI	41	14,981	105,446	-305,489	221,192	4,868	41,945	-77,656	155,711	10,114	102,264	-303,855	270,850

Table 5. Monetary Value of Abnormal Weather on Revenues, Costs, and Net Returns, 1964-1984 vs. 1985-2004 (in thousands 1996 dollars)

	Pacific Region			*Central Region*							
	CA	OR	WA	IA	IL	IN	MI	MN	MO	OH	WI
$P(Y - Y^e)$											
1st half: 1964-1984											
Mean	-42,051	2,066	3,730	-67,444	-25,495	-20,403	-752	-44,992	-61,009	-4,929	-10,249
StDev	180,724	16,404	19,924	362,692	452,232	188,592	58,292	212,993	321,397	113,205	78,920
2nd half: 1985-2004											
Mean	13,836	-6,401	-7,459	135,996	76,485	33,920	8,605	117,211	58,384	15,429	39,010
StDev	409,365	29,145	48,307	596,561	703,709	283,429	132,215	269,435	329,026	225,539	122,792
p-value ANOVA	0.5784	0.2619	0.3427	0.1974	0.5862	0.4766	0.7729	0.0394**	0.2473	0.719	0.1367
p-value KF	0.0004***	0.0173**	0.0020***	0.0239**	0.0468**	0.0743*	0.1199	0.4696	0.1188	0.0059***	0.1188
$W(X - X^e)$											
1st half: 1964-1984											
Mean	12,167	2,137	972	-2,556	-957	-402	-846	-2,756	-576	2,644	-1,195
StDev	57,846	9,543	13,867	57,019	33,381	17,925	10,531	42,321	22,730	17,754	27,220
2nd half: 1985-2004											
Mean	-59,827	-5,533	-4,523	16,474	6,509	2,960	2,489	12,673	2,404	-4,094	10,642
StDev	184,495	26,259	41,482	86,625	40,192	26,487	28,435	75,829	30,877	26,600	52,375
p-value ANOVA	0.1033	0.2259	0.5767	0.4136	0.5225	0.6385	0.6248	0.4292	0.7279	0.3485	0.3731
p-value KF	0.0017***	0.0404**	0.0124**	0.1803	0.5171	0.1581	0.0051***	0.0627*	0.2549	0.1076	0.0356**
IAW											
1st half: 1964-1984											
Mean	-54,218	-70	2,758	-64,889	-24,538	-20,002	94	-42,237	-60,433	-7,574	-9,054
StDev	196,323	16,478	23,757	357,264	451,026	189,841	59,532	199,079	314,434	115,907	76,199
2nd half: 1985-2004											
Mean	73,663	-869	-2,937	119,522	69,976	30,961	6,116	104,538	55,979	19,523	28,368
StDev	488,993	34,964	40,948	569,491	687,336	271,994	127,061	254,403	321,834	219,570	121,172
p-value	0.2831	0.9266	0.5915	0.2243	0.6076	0.4928	0.8482	0.0471**	0.2488	0.6266	0.2464
p-value KF	0.0091***	0.0287**	0.0538*	0.02223**	0.0377**	0.0318**	0.1737	0.4927	0.0837*	0.0083***	0.2697

Note : p-value ANOVA (KF, Fligner-Killeen) shows the level of significance of the F (Chi-square) Test comparing the means (variances) of the series across the two periods. Significance codes: *** 0.01; ** 0.05; * 0.10.

Table 6a. Parameter Estimates from Input Distance Function, Pacific Region

Par.	Model 1: Original Variables		Model 2: Weather-Filtered Variables		Par.	Model 1: Original Variables		Model 2: Weather-Filtered Variables	
	Mean (StDev)	Median [Credible Interval]	Mean (StDev)	Median [Credible Interval]		Mean (StDev)	Median [Credible Interval]	Mean (StDev)	Median [Credible Interval]
α_H	-0.6184 (0.4347)	-0.5937 [-1.545;0.1963]	-0.1263 (0.4342)	-0.1133 [-1.0347;0.6822]	δ_{VA}	-0.1187 (0.0826)	-0.1117 [-0.295;0.0311]	-0.1338 (0.0655)	-0.1301* [-0.2705;-0.0152]
α_V	0.9394 (0.7933)	0.9239 [-0.5703;2.5532]	1.1065 (0.6568)	1.0889 [-0.1858;2.4106]	δ_{OA}	-0.1153 (0.07)	-0.1099 [-0.2637;0.0013]	-0.0022 (0.0376)	0.0014 [-0.0867;0.0599]
α_O	0.628 (0.4487)	0.6257 [-0.2459;1.5357]	-0.3179 (0.3394)	-0.3237 [-0.9607;0.3902]	$\alpha_{H\Theta}$	-0.01 (0.6234)	-0.0125 [-0.1709;0.1396]	-0.0505 (7.8965)	0.04 [-1.7249;1.6653]
α_{HH}	0.0291 (0.0266)	0.0214* [0.0007;0.0985]	0.0261 (0.0244)	0.0191* [0.0008;0.0918]	$\alpha_{V\Theta}$	0.029 (0.8353)	0.0375 [-0.2119;0.2585]	-0.1176 (5.2685)	-0.0634 [-1.7413;1.5162]
α_{HV}	-0.0226 (0.032)	-0.0123 [-0.1102;0.0123]	-0.0201 (0.0298)	-0.0107 [-0.1008;0.0141]	$\alpha_{O\Theta}$	0.0727 (0.3244)	0.0728 [-0.0378;0.2253]	0.0352 (4.2404)	0.0112 [-1.2527;1.3365]
α_{HO}	0.0029 (0.021)	0.0017 [-0.0402;0.0477]	0.0003 (0.0147)	0.0001 [-0.0302;0.0315]	$\beta_{K\Theta}$	-0.1917 (1.0027)	-0.1728 [-0.5268;0.0972]	0.0341 (20.599)	-0.4537 [-5.9578;5.4129]
α_{VV}	0.0717 (0.0626)	0.0543* [0.0022;0.2327]	0.0809 (0.0631)	0.0683* [0.003;0.2375]	$\beta_{L\Theta}$	0.072 (1.0634)	0.0398 [-0.1358;0.5326]	-0.23 (17.272)	0.2339 [-3.9403;3.8073]
α_{VO}	-0.0142 (0.0387)	-0.0074 [-0.1104;0.0525]	-0.0153 (0.0286)	-0.0086 [-0.0877;0.0282]	$\beta_{A\Theta}$	-0.1953 (0.7489)	-0.1965 [-0.4994;0.0033]	0.1147 (10.6912)	-0.1308 [-1.4767;1.3945]
α_{OO}	0.0759 (0.0563)	0.0661* [0.0028;0.2114]	0.0398 (0.0346)	0.0306* [0.0013;0.1293]	$\sigma_{\ln D}$	0.0304 (0.0058)	0.0298* [0.0212;0.0437]	0.0386 (0.006)	0.0382* [0.0282;0.0515]
β_K	0.3525 (0.9093)	0.2525 [-1.2004;2.3026]	1.9488 (0.64)	1.9373* [0.7252;3.2296]	*Mean* $\lambda_{63:04}$	-0.6103 (0.342)	-0.678 [-1.164;0.0728]	-0.0774 (0.1651)	-0.0661 [-0.4314;0.2317]
β_L	0.0727 (0.4677)	0.0665 [-0.8704;0.9726]	-0.2933 (0.39)	-0.2977 [-1.0609;0.4972]	*Corr.* $\vartheta_{st},\vartheta_{st}^K$	0.6795 (0.1073)	0.6911* [0.4343;0.8514]	0.7251 (0.0926)	0.7385* [0.5147;0.868]
β_A	-1.3377 (0.9196)	-1.3965 [-3.0813;0.4559]	-0.0293 (0.7568)	0.0291 [-1.6499;1.2958]	*Corr.* $\vartheta_{st},\vartheta_{st}^L$	-0.0431 (0.187)	-0.0406 [-0.4183;0.3156]	-0.1742 (0.1661)	-0.1721 [-0.4967;0.1495]
β_{KK}	-0.1462 (0.1216)	-0.1146* [-0.4462;-0.0047]	-0.1798 (0.1191)	-0.1601* [-0.4598;-0.0106]	*Corr.* $\vartheta_{st},\vartheta_{st}^A$	-0.0576 (0.1688)	-0.0573 [-0.389;0.2617]	0.0216 (0.1501)	0.026 [-0.2675;0.3108]
β_{LL}	-0.0721 (0.0604)	-0.0567* [-0.2271;-0.0025]	-0.0434 (0.041)	-0.0312* [-0.1542;-0.0009]	Log Likel.	1258.77 (19.58)	1258.8* [1220.39;1297]	1249.91 (15.95)	1250.38* [1217.28;1279.77]
β_{AA}	0.318 (0.1438)	0.3225* [0.0522;0.6015]	0.1657 (0.0911)	0.1618 [-0.0035;0.3563]					
β_{KL}	0.0278 (0.0613)	0.0143 [-0.0672;0.1842]	0.0146 (0.0452)	0.0056 [-0.0562;0.1259]	Recov. Param.				
β_{KA}	0.1024 (0.1272)	0.1145 [-0.1368;0.3279]	-0.1215 (0.0645)	-0.1216 [-0.2469;0.0006]	β_M	0.5748 (0.9881)	0.7132 [-1.5197;2.1818]	-0.6555 (0.5606)	-0.6349 [-1.8193;0.3932]
β_{LA}	0.0182 (0.0649)	0.0139 [-0.097;0.1565]	0.0435 (0.051)	0.0425 [-0.0535;0.1444]	$\beta_{M\Theta}$	0.1197 (0.6203)	0.1296 [-0.2225;0.3361]	0.1959 (6.3453)	0.1955 [-2.1066;2.6119]
δ_{HL}	0.0563 (0.0488)	0.0536 [-0.0318;0.1592]	0.1291 (0.051)	0.1294* [0.0307;0.2279]	β_{MM}	-0.1625 (0.1279)	-0.1288* [-0.4829;-0.0114]	-0.194 (0.1143)	-0.1813* [-0.4512;-0.0213]
δ_{VL}	-0.0767 (0.0828)	-0.0723 [-0.2438;0.0762]	-0.159 (0.0668)	-0.1606* [-0.2897;-0.0238]	β_{LM}	0.0442 (0.0576)	0.0356 [-0.0486;0.1784]	0.0288 (0.0465)	0.0219 [-0.0484;0.1353]
δ_{OL}	0.0101 (0.0572)	0.0121 [-0.1101;0.1178]	0.0195 (0.0485)	0.018 [-0.0717;0.1182]	β_{MA}	-0.1206 (0.1312)	-0.1364 [-0.3475;0.1168]	0.0781 (0.0548)	0.0777 [-0.029;0.1876]
δ_{HK}	-0.0165 (0.0659)	-0.0155 [-0.1499;0.112]	-0.136 (0.0569)	-0.1377* [-0.2444;-0.0191]	β_{KM}	0.1183 (0.1156)	0.0859 [-0.0172;0.4124]	0.1652 (0.1094)	0.1516* [0.0046;0.4151]
δ_{VK}	-0.0212 (0.1209)	-0.0175 [-0.2599;0.205]	0.11 (0.083)	0.1139 [-0.0646;0.2619]	δ_{HM}	-0.0398 (0.0516)	-0.0375 [-0.1484;0.0577]	0.0068 (0.0444)	0.0085 [-0.0844;0.0921]
δ_{OK}	-0.0762 (0.0815)	-0.0757 [-0.2403;0.0838]	0.0225 (0.059)	0.0212 [-0.0931;0.1398]	δ_{VM}	0.098 (0.0946)	0.0944 [-0.0807;0.2898]	0.049 (0.0715)	0.0479 [-0.0861;0.1953]
δ_{HA}	0.0258 (0.0421)	0.0244 [-0.0535;0.1142]	-0.0194 (0.038)	-0.02 [-0.0902;0.0583]	δ_{OM}	0.066 (0.0832)	0.0625 [-0.0862;0.2293]	-0.042 (0.0509)	-0.0399 [-0.1482;0.0535]

Table 6b. Parameter Estimates from Input Distance Function, Central Region

Par.	Model 1: Original Variables Mean (StDev)	Model 1: Original Variables Median [Credible Interval]	Model 2: Weather-Filtered Variables Mean (StDev)	Model 2: Weather-Filtered Variables Median [Credible Interval]	Par.	Model 1: Original Variables Mean (StDev)	Model 1: Original Variables Median [Credible Interval]	Model 2: Weather-Filtered Variables Mean (StDev)	Model 2: Weather-Filtered Variables Median [Credible Interval]
α_H	0.1981	0.2009	-1.2035	-1.1984*	δ_{VA}	-0.0832	-0.0837	-0.0934	-0.0933
	(0.4122)	[-0.6031;0.9999]	(0.5432)	[-2.2742;-0.148]		(0.062)	[-0.2032;0.0388]	(0.0577)	[-0.2117;0.0185]
α_V	0.345	0.3515	0.3909	0.3961	δ_{OA}	-0.0384	-0.0385	-0.0201	-0.0200
	(0.811)	[-1.265;1.9001]	(0.7422)	[-1.0785;1.8138]		(0.0195)	[-0.077;0.0004]	(0.0182)	[-0.0559;0.0158]
α_O	0.5352	0.539*	0.2707	0.2729	$\alpha_{H\Theta}$	-0.0647	-0.0606	1.2303	-0.0607
	(0.2552)	[0.0118;1.029]	(0.2456)	[-0.2193;0.7489]		(0.3846)	[-0.1836;0.0036]	(91.8585)	[-0.1994;0.0236]
α_{HH}	0.0114	0.0083*	0.0102	0.0074*	$\alpha_{V\Theta}$	0.1069	0.0996*	-1.7735	0.0983*
	(0.0105)	[0.0003;0.0393]	(0.0094)	[0.0003;0.0349]		(1.0688)	[0.0418;0.3647]	(141.8937	[0.0405;0.4189]
α_{HV}	0.0051	0.0035	0.0043	0.0028	$\alpha_{O\Theta}$	0.0683	0.0600*	-0.8121	0.0583*
	(0.0095)	[-0.0113;0.0269]	(0.0104)	[-0.0147;0.0288]		(0.5209)	[0.0135;0.2441]	(64.866)	[0.0103;0.268]
α_{HO}	-0.0016	-0.001	-0.0012	-0.0007	$\beta_{K\Theta}$	0.1294	0.1215*	-1.3914	0.1144*
	(0.0055)	[-0.0139;0.0095]	(0.0052)	[-0.0134;0.0089]		(1.4606)	[0.0111;0.5074]	(119.7068	[0.0075;0.5219]
α_{VV}	0.0434	0.0389*	0.0505	0.0457*	$\beta_{L\Theta}$	-0.123	-0.1143*	1.5475	-0.1381*
	(0.0295)	[0.0022;0.1122]	(0.0339)	[0.0029;0.1273]		(0.5471)	[-0.3052;-0.0495]	(125.1516	[-0.4241;-0.0689]
α_{VO}	-0.011	-0.0093	-0.0104	-0.0083	$\beta_{A\Theta}$	-0.1939	-0.1817*	1.4815	-0.1747*
	(0.0102)	[-0.0342;0.0035]	(0.0102)	[-0.0343;0.0041]		(1.4635)	[-0.601;-0.0826]	(130.7939	[-0.6614;-0.0625]
α_{OO}	0.0124	0.0102*	0.0111	0.0089*	$\sigma_{\ln D}$	0.1051	0.1046*	0.1143	0.1146*
	(0.0098)	[0.0005;0.0372]	(0.0092)	[0.0004;0.0341]		(0.0112)	[0.0844;0.1278]	(0.0127)	[0.089;0.1377]
β_K	1.6917	1.6829*	1.5915	1.5783*	*Mean*	0.1047	0.1034(*50%)	0.088	0.0883(*48%)
	(0.6953)	[0.2929;3.0496]	(0.7248)	[0.1646;3.001]	$\lambda_{63:04}$	(0.1040)	[-0.0956;0.3110]	(0.1084)	[-0.1235;0.2999]
β_L	0.6767	0.6624	0.7004	0.6936	*Corr.*	0.8045	0.8156*	0.8889	0.8952*
	(0.4624)	[-0.1847;1.6121]	(0.4732)	[-0.2234;1.6112]	$\vartheta_{st},\vartheta_{st}^K$	(0.0675)	[0.6438;0.9024]	(0.0368)	[0.7986;0.9418]
β_A	-0.588	-0.5725	0.7689	0.8067	*Corr.*	-0.1717	-0.17	-0.0955	-0.0938
	(2.6144)	[-5.8672;4.5311]	(2.2777)	[-3.7711;5.184]	$\vartheta_{st},\vartheta_{st}^L$	(0.1229)	[-0.416;0.0655]	(0.1055)	[-0.304;0.1082]
β_{KK}	-0.0485	-0.0373*	-0.0455	-0.0349*	*Corr.*	-0.1262	-0.1214	0.0419	0.0454
	(0.0416)	[-0.1548;-0.0018]	(0.0398)	[-0.148;-0.0017]	$\vartheta_{st},\vartheta_{st}^A$	(0.1146)	[-0.3609;0.0856]	(0.0895)	[-0.1434;0.2056]
β_{LL}	-0.0184	-0.0141*	-0.0144	-0.0109*	Log	2565.00	2565.40*	2567.35	2567.70*
	(0.0158)	[-0.059;-0.0006]	(0.0129)	[-0.048;-0.0004]	Likel.	(13.43)	[2537.47;2590.14]	(13.85)	[2538.88;2593.6]
β_{AA}	0.2394	0.2329	0.0109	0.0016					
	(0.2181)	[-0.1681;0.6802]	(0.1873)	[-0.3528;0.3905]					
β_{KL}	-0.0067	-0.0048	-0.0038	-0.0026	Recov.				
	(0.0148)	[-0.0407;0.0215]	(0.0132)	[-0.0331;0.023]	Param.				
β_{KA}	-0.2011	-0.2011*	-0.1565	-0.1559*	β_M	-1.3685	-1.3701	-1.2919	-1.2922
	(0.0666)	[-0.3324;-0.0707]	(0.0699)	[-0.2984;-0.0199]		(0.7229)	[-2.8068;0.0475]	(0.748)	[-2.742;0.1761]
β_{LA}	0.0475	0.0463	0.0061	0.0043	$\beta_{M\Theta}$	-0.0064	-0.0066	-0.1561	0.0238
	(0.0491)	[-0.0464;0.1478]	(0.0505)	[-0.0855;0.1125]		(0.941)	[-0.257;0.0916]	(8.5616)	[-0.1796;0.1286]
δ_{HL}	0.0004	0.0006	0.0152	0.0154	β_{MM}	-0.0802	-0.0667*	-0.0674	-0.0551*
	(0.0237)	[-0.0453;0.0464]	(0.0284)	[-0.0412;0.0702]		(0.0591)	[-0.2227;-0.0053]	(0.0527)	[-0.1951;-0.0043]
δ_{VL}	-0.0266	-0.0257	-0.0371	-0.0359	β_{LM}	0.025	0.0196	0.0182	0.0137
	(0.021)	[-0.0688;0.0135]	(0.0211)	[-0.0809;0.0012]		(0.0239)	[-0.0064;0.0833]	(0.0198)	[-0.0083;0.0687]
δ_{OL}	-0.0643	-0.0643*	-0.0253	-0.0248	β_{MA}	0.1535	0.1544*	0.1505	0.1506*
	(0.0238)	[-0.1113;-0.0188]	(0.0214)	[-0.0688;0.0149]		(0.06)	[0.0341;0.2686]	(0.0596)	[0.0304;0.2635]
δ_{HK}	0.0162	0.0165	0.0054	0.0048	β_{KM}	0.0551	0.0435	0.0492	0.0378
	(0.0344)	[-0.0512;0.0833]	(0.0408)	[-0.0744;0.0884]		(0.0471)	[-0.0005;0.1712]	(0.0435)	[-0.0005;0.1598]
δ_{VK}	0.003	0.0033	0.0105	0.0111	δ_{HM}	-0.0166	-0.0168	-0.0206	-0.021
	(0.0399)	[-0.077;0.0809]	(0.0398)	[-0.0685;0.0858]		(0.0327)	[-0.0806;0.048]	(0.0351)	[-0.0899;0.0505]
δ_{OK}	0.081	0.0809*	0.0413	0.0418	δ_{VM}	0.0236	0.0235	0.0265	0.0257
	(0.0262)	[0.0296;0.1329]	(0.0264)	[-0.0095;0.0927]		(0.0369)	[-0.0496;0.0952]	(0.0377)	[-0.0456;0.1037]
δ_{HA}	-0.0439	-0.0439	0.0593	0.0589	δ_{OM}	-0.0167	-0.0162	-0.0159	-0.0152
	(0.0315)	[-0.1063;0.0167]	(0.0414)	[-0.0236;0.1394]		(0.0236)	[-0.0633;0.0297]	(0.0242)	[-0.0629;0.0313]

Table 7. Descriptive statistics of the Annual Median Estimates of the Scale Effect, $\widehat{SE}$ (in percent)

State	Model 1: Original Variables		Model 2: Weather-Filtered Variables	
	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]
CA	0.62 (2.5)	0.81 [-10.68; 5.41]	1.22 (2.41)	0.82 [-2.67; 8.09]
OR	0.58 (1.7)	-0.05 [-3.69; 4.28]	1.53 (2.62)	1.62 [-3.91; 7.28]
WA	1.21 (2.68)	0.63 [-4.58; 6.34]	1.79 (4.03)	1.66 [-9.19; 8.89]
IA	0.84 (6.76)	0.5 [-19.09; 20.66]	0.59 (4.19)	0.99 [-11.21; 9.23]
IL	0.24 (3.78)	-0.46 [-9.17; 7.13]	0.02 (1.95)	0.1 [-5.02; 5.48]
IN	1.03 (6.01)	1.44 [-10.5; 22.89]	0.52 (3.33)	0.57 [-6.95; 8.5]
MI	1.22 (9.39)	1.32 [-17.1; 53.9]	0.59 (3.1)	0.61 [-6.6; 10.53]
MN	1.64 (9.83)	0.61 [-22.5; 42.59]	0.96 (3.7)	0.71 [-8.4; 11.55]
MO	0.84 (5.36)	-0.15 [-9.38; 19.04]	0.41 (2.8)	0.82 [-5.85; 6.65]
OH	0.47 (4.59)	0.25 [-12.72; 13.85]	0.34 (2.97)	-0.14 [-6.12; 7.1]
WI	1.93 (14.4)	0.48 [-21.52; 74.52]	0.55 (4.3)	0.41 [-6.91; 10.31]

Table 8. Descriptive statistics of the Annual Median Estimates of the Markup Effect, $\widehat{MUE}$ (in percent)

State	Model 1: Original Variables		Model 2: Weather-Filtered Variables	
	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]
CA	0.73 (5.42)	1.31 [-13.45; 16.66]	0.10 (1.39)	0.18 [-4.04; 3.67]
OR	0.83 (3.43)	1.03 [-11.62; 8.14]	-0.40 (2.73)	0.01 [-7.09; 5.53]
WA	0.32 (4.11)	0.72 [-10.39; 8.25]	-0.33 (4.08)	0.12 [-11.59; 8.53]
IA	-0.54 (2.59)	-0.15 [-8.28; 4.18]	-0.18 (1.96)	-0.05 [-6.75; 5.54]
IL	0.45 (7.15)	0.73 [-21.04; 16.74]	0.66 (4.4)	1.08 [-12.65; 14.81]
IN	-0.35 (4.63)	0.42 [-14.9; 8.67]	0.15 (1.99)	0.40 [-4.17; 7.28]
MI	-0.30 (10.58)	0.35 [-61.89; 18.48]	-0.02 (2.61)	0.25 [-14.34; 5.52]
MN	-1.19 (9.38)	0.01 [-49.52; 22.11]	-0.35 (2.82)	0.30 [-7.61; 3.83]
MO	-0.54 (3.17)	-0.17 [-11.97; 6.96]	-0.16 (1.42)	-0.25 [-3.54; 3.04]
OH	0.08 (3.71)	1.10 [-10.2; 5.79]	0.09 (2.28)	0.10 [-4.67; 4.2]
WI	-1.72 (15.25)	-0.23 [-84.09; 25.92]	-0.37 (3.68)	0.32 [-14.53; 6.42]

Table 9. Descriptive statistics of the Annual Median Estimates of Adjusted Technical Change, $\frac{C_v(w_v,X_v)}{C_o(w,X)}\widehat{TC}$ (in percent)

State	Model 1: Original Variables		Model 2: Weather-Filtered Variables	
	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]
CA	1.90 (5.66)	2.32 [-11.09; 21.61]	0.60 (4.42)	0.54 [-10.98; 9.43]
OR	1.97 (6.55)	2.25 [-14.9; 28.32]	0.67 (4.74)	0.23 [-11.76; 9.94]
WA	1.45 (4.9)	2.02 [-10.68; 19.5]	0.74 (4.64)	0.68 [-10.74; 10.21]
IA	-0.16 (2.16)	-0.19 [-4.1; 7.49]	-0.01 (1.28)	-0.06 [-2.52; 3.89]
IL	-0.50 (3.61)	-0.82 [-6.56; 9.69]	-0.42 (2.45)	-0.96 [-4.27; 5.73]
IN	-0.20 (2.42)	-0.26 [-4.97; 7.81]	-0.11 (1.60)	-0.26 [-2.83; 4.37]
MI	-0.06 (1.73)	-0.1 [-3.51; 5.34]	0.03 (1.24)	-0.12 [-2.26; 3.53]
MN	-0.08 (2.19)	-0.02 [-4.80; 5.66]	0.05 (1.51)	-0.04 [-2.94; 3.29]
MO	-0.23 (2.78)	-0.25 [-5.22; 8.67]	-0.08 (1.86)	-0.10 [-3.11; 5.10]
OH	-0.23 (3.12)	-0.34 [-5.97; 10.44]	-0.10 (1.95)	-0.20 [-3.57; 5.60]
WI	0.17 (1.24)	0.08 [-2.60; 2.68]	0.36 (5.73)	0.08 [-1.84; 2.84]

Table 10. Descriptive statistics of the Annual Median Estimates of Adjusted Technical Efficiency Change, $\frac{C_v(w_v,X_v)}{C_o(w,X)}\widehat{\dot{TE}}$ (in percent)

State	Model 1: Original Variables		Model 2: Weather-Filtered Variables	
	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]
CA	-0.40	-0.39	-0.05	-0.04
	(0.03)	[-0.45; -0.35]	(0.06)	[-0.16; 0.05]
OR	-0.52	-0.46	0.02	0.01
	(0.66)	[-1.65; 0.61]	(0.06)	[-0.08; 0.14]
WA	-0.29	-0.27	-0.03	-0.03
	(0.07)	[-0.42; -0.18]	(0.22)	[-0.42; 0.34]
IA	1.13	1.09	0.93	0.90
	(1.07)	[-0.74; 2.95]	(0.92)	[-0.68; 2.49]
IL	1.14	1.10	0.96	0.94
	(1.13)	[-0.88; 3.04]	(1.06)	[-0.94; 2.75]
IN	1.40	1.36	1.35	1.30
	(1.24)	[-0.79; 3.47]	(1.11)	[-0.61; 3.23]
MI	1.44	1.39	1.44	1.39
	(0.71)	[0.22; 2.58]	(0.54)	[0.52; 2.3]
MN	0.94	0.90	0.66	0.64
	(0.76)	[-0.36; 2.20]	(0.67)	[-0.50; 1.77]
MO	1.11	1.07	0.80	0.78
	(1.3)	[-1.17; 3.27]	(1.23)	[-1.36; 2.83]
OH	1.52	1.47	1.41	1.37
	(1.15)	[-0.48; 3.41]	(1.06)	[-0.44; 3.18]
WI	0.95	0.92	0.74	0.71
	(0.29)	[0.41; 1.48]	(11.58)	[0.38; 1.08]

Table 11. Descriptive statistics of the Annual Median Estimates of Adjusted Allocative Efficiency Change, $\frac{C_v(w_v,X_v)}{C_o(w,X)}\widehat{\dot{AE}}$ (in percent)

State	Model 1: Original Variables		Model 2: Weather-Filtered Variables	
	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]
CA	-1.28 (4.40)	-0.87 [-15.54; 7.15]	-0.71 (3.56)	-0.52 [-9.05; 6.92]
OR	-0.37 (5.94)	0.08 [-15.02; 25.54]	0.33 (3.73)	0.35 [-6.4; 8.45]
WA	-1.00 (3.98)	-1.24 [-13.43; 7.84]	-0.56 (3.37)	-1.02 [-8.33; 5.43]
IA	-0.30 (4.01)	0.08 [-13.18; 11.01]	-0.33 (4.02)	-0.03 [-15.44; 9.06]
IL	-0.10 (2.78)	-0.15 [-5.93; 6.40]	-0.05 (2.59)	-0.21 [-5.79; 6.17]
IN	-0.34 (3.04)	0.08 [-6.28; 5.98]	-0.38 (3.25)	-0.36 [-8.22; 5.35]
MI	-0.23 (4.36)	0.10 [-9.06; 8.8]	-0.18 (4.47)	0.01 [-9.26; 9]
MN	-0.42 (3.93)	-0.21 [-10.87; 8.11]	-0.28 (3.62)	0.33 [-8.96; 8.76]
MO	-0.20 (5.02)	0.07 [-13.25; 11.05]	-0.11 (4.47)	-0.42 [-10.59; 10.11]
OH	-0.27 (4.32)	-0.83 [-11.27; 8.61]	-0.32 (4.73)	0.03 [-11.69; 8.37]
WI	-0.77 (5.43)	-0.04 [-18.2; 10.98]	-0.68 (11.87)	-0.54 [-19.6; 7.41]

Table 12. Descriptive statistics of the negative of the Annual Median Estimates of the Quasi-fixed Input Effect, $-\widehat{QFIE}$ (in percent)

State	Model 1: Original Variables		Model 2: Weather-Filtered Variables	
	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]
CA	-0.17 (0.18)	-0.13 [-0.6; 0.11]	0.06 (0.08)	0.05 [-0.11; 0.24]
OR	-0.25 (0.43)	-0.05 [-1.25; 0.44]	-0.02 (0.1)	0 [-0.35; 0.13]
WA	-0.16 (0.27)	-0.04 [-0.87; 0.13]	0.03 (0.09)	0.03 [-0.14; 0.24]
IA	-0.01 (0.06)	-0.02 [-0.14; 0.12]	0.00 (0.04)	0.00 [-0.08; 0.12]
IL	-0.07 (0.16)	-0.02 [-0.48; 0.29]	-0.04 (0.09)	-0.01 [-0.26; 0.1]
IN	-0.07 (0.13)	-0.04 [-0.47; 0.19]	-0.05 (0.09)	-0.03 [-0.33; 0.13]
MI	-0.19 (0.37)	-0.03 [-1; 0.3]	-0.15 (0.28)	-0.08 [-0.77; 0.25]
MN	-0.11 (0.3)	-0.09 [-0.78; 0.54]	-0.05 (0.17)	-0.01 [-0.46; 0.28]
MO	-0.07 (0.33)	-0.02 [-1.07; 0.34]	-0.03 (0.18)	0.00 [-0.63; 0.25]
OH	-0.13 (0.26)	-0.03 [-0.94; 0.31]	-0.08 (0.16)	-0.04 [-0.52; 0.15]
WI	0.16 (0.23)	0.08 [-0.23; 0.76]	-0.08 (0.13)	-0.05 [-0.41; 0.17]

Table 13. Descriptive statistics of the negative of the Annual Median Estimates of the Input Price Effect, -$\widehat{IPF}$ (in percent)

State	Model 1: Original Variables		Model 2: Weather-Filtered Variables	
	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]
CA	0.19 (2.3)	0.41 [-5.72; 6.92]	0.14 (1.29)	0.11 [-2.29; 3.29]
OR	0.26 (2.12)	-0.03 [-3.33; 4.27]	0.24 (1.92)	-0.06 [-3.69; 4.77]
WA	0.24 (1.95)	0.33 [-4.3; 5.78]	0.17 (2)	0.24 [-5.87; 5.14]
IA	0.15 (2.01)	0.35 [-5.81; 6.09]	0.19 (2.06)	0.16 [-5.1; 7.18]
IL	0.08 (1.49)	0.27 [-4.85; 3.34]	0.03 (1.39)	0.32 [-4.24; 2.85]
IN	0.07 (1.84)	0.09 [-3.25; 5]	0.05 (1.91)	0.05 [-3.69; 6.44]
MI	-0.16 (3.81)	0.09 [-10.33; 8.96]	-0.27 (3.37)	0.03 [-7.67; 6.65]
MN	0.41 (3.17)	0.28 [-10.52; 7.06]	0.37 (2.79)	0.3 [-8.78; 6.48]
MO	-0.13 (3.36)	-0.06 [-11.42; 10.95]	-0.13 (2.9)	0.2 [-8.39; 9.01]
OH	0.2 (2.42)	0.15 [-6.09; 5.8]	0.13 (2.58)	0.3 [-6.46; 5.04]
WI	0.63 (3.24)	0.22 [-4.36; 15.9]	0.6 (2.87)	0.06 [-4.99; 13.54]

Table 14. Descriptive statistics of the Annual Median Estimates of the Output Price Aggregate Effect, $\widehat{OPAE}$ (in percent)

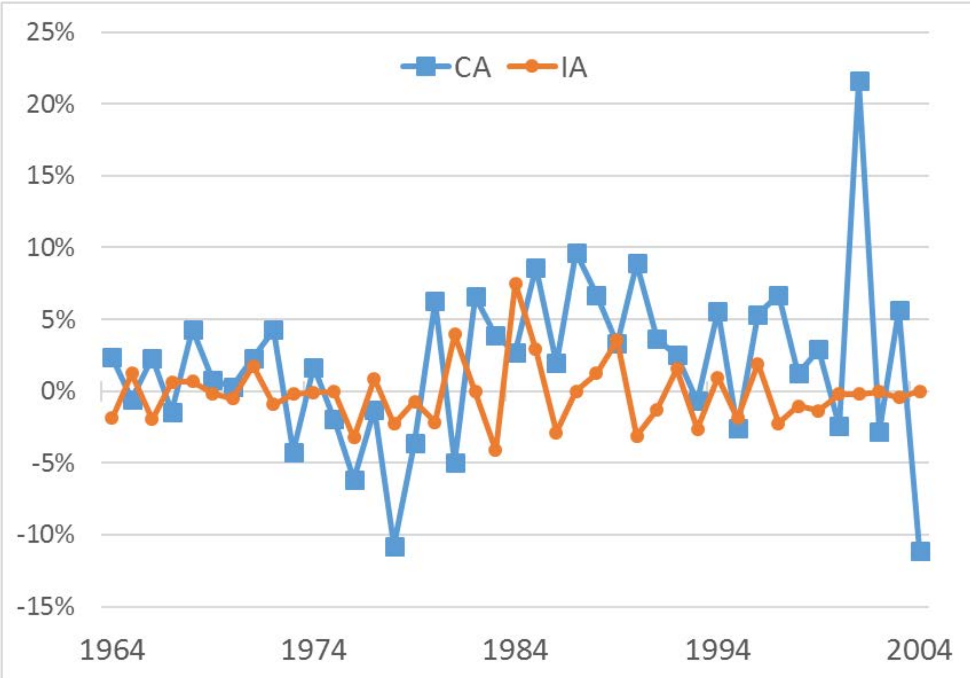
State	Model 1: Original Variables		Model 2: Weather-Filtered Variables	
	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]
CA	-0.05 (0.10)	-0.02 [-0.47; 0.08]	-0.10 (1.88)	0.32 [-4.68; 2.98]
OR	-0.12 (0.27)	-0.03 [-1.52; 0.07]	0.02 (3.61)	0.20 [-8.16; 7.52]
WA	-0.11 (0.18)	-0.03 [-0.69; 0.06]	-0.03 (4.04)	-0.37 [-11.77; 7.91]
IA	-0.10 (0.24)	-0.05 [-0.71; 0.57]	0 (1.43)	-0.15 [-2.68; 3.92]
IL	-0.03 (0.27)	-0.03 [-0.89; 0.83]	0.08 (2.44)	0.27 [-4.84; 4.85]
IN	-0.01 (0.30)	-0.01 [-1.15; 1.19]	0.01 (1.93)	0.37 [-4.91; 4.17]
MI	-0.07 (0.14)	-0.03 [-0.58; 0.11]	0.01 (1.11)	-0.07 [-3.00; 1.82]
MN	-0.08 (0.48)	-0.02 [-2.53; 0.56]	-0.07 (1.36)	0.01 [-3.24; 2.94]
MO	-0.03 (0.27)	-0.01 [-1.16; 0.81]	0.07 (3.46)	0.44 [-11.00; 8.59]
OH	-0.05 (0.24)	-0.03 [-1.41; 0.37]	0.02 (1.77)	0.04 [-3.74; 4.02]
WI	-0.07 (0.28)	-0.05 [-0.87; 0.73]	-0.01 (1.33)	-0.19 [-2.80; 2.47]

Table 15. Descriptive statistics of the negative of the Annual Median Estimates of the Input Price Aggregate Effect, $-\widehat{IPAE}$ (in percent)

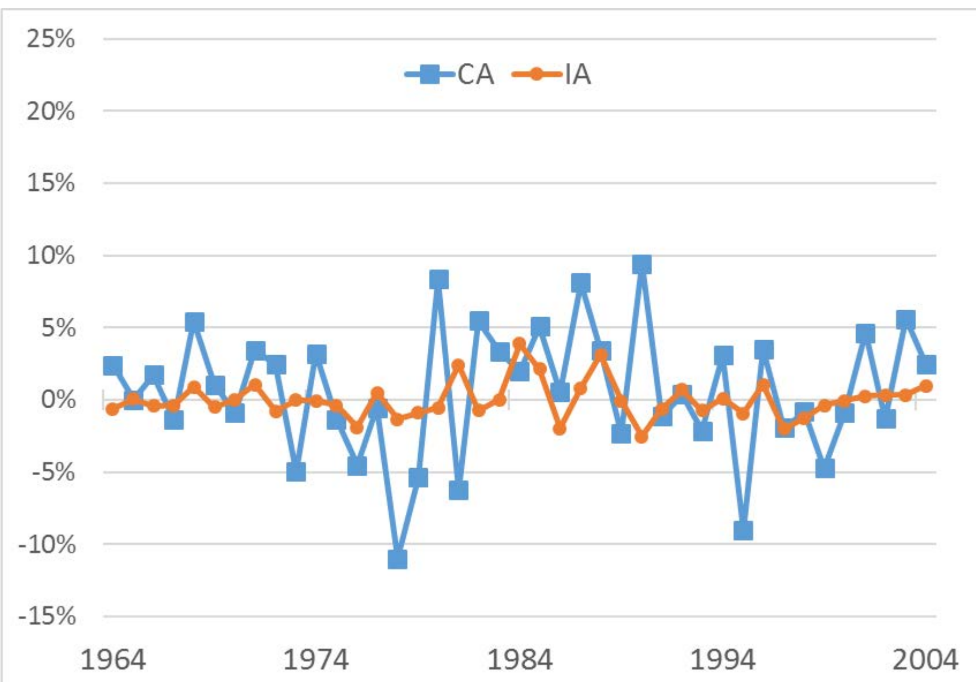
State	Model 1: Original Variables		Model 2: Weather-Filtered Variables	
	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]
CA	0.22 (0.44)	0.07 [-0.19; 2.53]	0.30 (1.8)	0.49 [-4.24; 3.92]
OR	0.26 (0.48)	0.13 [-0.05; 2.83]	0.25 (1.46)	0.25 [-4.04; 3.21]
WA	-0.13 (1.32)	0.14 [-5.04; 3.03]	-0.15 (1.74)	-0.02 [-4.44; 3.71]
IA	0.41 (0.55)	0.23 [-0.02; 3.07]	0.44 (3.22)	0.52 [-6.72; 6.18]
IL	0.40 (0.72)	0.23 [-0.01; 4.23]	0.38 (3.33)	-0.22 [-5.25; 7.78]
IN	0.41 (0.62)	0.25 [-0.04; 3.7]	0.33 (2.78)	0.39 [-5.18; 6.96]
MI	0.58 (0.98)	0.33 [-0.09; 5.89]	0.50 (2.98)	0.18 [-7.88; 7.65]
MN	0.38 (0.55)	0.15 [-0.04; 2.72]	0.47 (3.8)	0.6 [-6.78; 8.99]
MO	0.49 (0.72)	0.22 [-0.04; 3.55]	0.51 (4.08)	0.69 [-10.21; 12.91]
OH	0.36 (0.55)	0.20 [-0.12; 2.89]	0.31 (2.84)	0.79 [-5.97; 5.28]
WI	0.36 (0.74)	0.19 [-0.09; 4.29]	0.31 (3.31)	0.71 [-6.78; 7.15]

Table 16. Descriptive statistics of the Annual Median Estimates of Total Factor Productivity Change, $\widehat{T\dot{F}P}$ (in percent)

State	$T\dot{F}P$ USDA		$\widehat{T\dot{F}P}$ Model 1: Original Variables		$\widehat{T\dot{F}P}^{WF}$ Model 2: Weather-Filtered Variables		$\widehat{T\dot{F}P} = \widehat{T\dot{F}P}^{WF} + \widehat{NWEFF}$ Model 2: Weather-Filtered Variables	
	Mean (StDev)	Correlation with USDA estimates [Range]	Mean Annual Median (StDev of Annual Medians)	Correlation with USDA estimates [Range of Annual Medians]	Mean Annual Median (StDev of Annual Medians)	Correlation with USDA estimates [Range of Annual Medians]	Mean Annual Median (StDev of Annual Medians)	Correlation with USDA estimates [Range of Annual Medians]
CA	1.66	1.00	1.76	0.991	1.57	0.842	1.67	0.996
	(6.12)	[-14.96; 11.58]	(6.39)	[-14.84; 11.81]	(5.84)	[-12.08; 11.28]	(6.17)	[-14.02; 11.47]
OR	2.57	1.00	2.64	0.99	2.65	0.824	2.52	0.995
	(5.67)	[-9.10; 16.57]	(5.68)	[-9.69; 16.27]	(7.52)	[-13.57; 17.52]	(5.76)	[-9.77; 17.21]
WA	1.55	1.00	1.53	0.991	1.64	0.757	1.55	0.995
	(4.78)	[-7.56; 11.73]	(4.88)	[-7.8; 12.46]	(7.03)	[-12.92; 13.58]	(4.84)	[-7.16; 12.56]
IA	1.79	1.00	1.42	0.992	1.62	0.834	1.65	0.998
	(10.86)	[-25.95; 33.13]	(10.73)	[-31.49; 27.38]	(8.61)	[-17.28; 20.33]	(10.82)	[-27.63; 30.54]
IL	1.86	1.00	1.62	0.998	1.62	0.719	1.89	0.999
	(13.42)	[-33.78; 32.67]	(13.1)	[-34.4; 31.13]	(9.93)	[-22.4; 20.75]	(13.36)	[-33.9; 32.41]
IN	2.11	1.00	1.95	0.998	1.86	0.787	2.13	0.999
	(11.92)	[-30.85; 33.7]	(11.77)	[-33.06; 30.65]	(9.2)	[-19.21; 22.24]	(11.87)	[-31.14; 33.16]
MI	2.28	1.00	2.24	0.995	1.95	0.706	2.13	0.998
	(6.37)	[-13.96; 18.75]	(6.52)	[-14.63; 19.57]	(6.63)	[-9.73; 14.07]	(6.55)	[-14.94; 19.45]
MN	1.84	1.00	1.50	0.995	1.76	0.83	1.56	0.995
	(9.72)	[-20.72; 27.61]	(9.78)	[-24.27; 27.8]	(8.62)	[-24.42; 17.15]	(9.66)	[-23.07; 28.06]
MO	1.52	1.00	1.24	0.997	1.27	0.487	1.43	0.999
	(10.47)	[-15.82; 24.66]	(10.45)	[-16.92; 23.67]	(9.55)	[-23.68; 23.21]	(10.37)	[-15.46; 24.3]
OH	2.08	1.00	1.95	0.998	1.80	0.757	2.02	0.999
	(9.81)	[-19.88; 31.00]	(9.66)	[-20.97; 29.97]	(8.26)	[-17.32; 21.33]	(9.77)	[-19.87; 30.44]
WI	1.56	1.00	1.32	0.995	1.42	0.703	1.39	0.997
	(5.68)	[-8.33; 14.84]	(5.66)	[-8.81; 14.29]	(6.53)	[-12.17; 17.47]	(5.75)	[-8.67; 15.14]

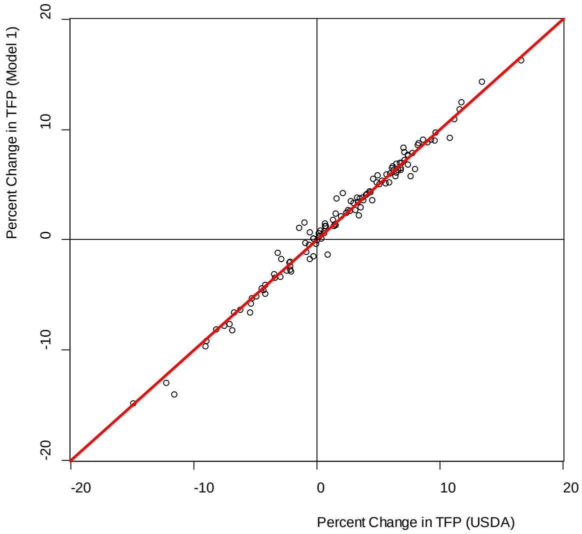


Panel a. Adjusted Technical Change estimates from Model 1

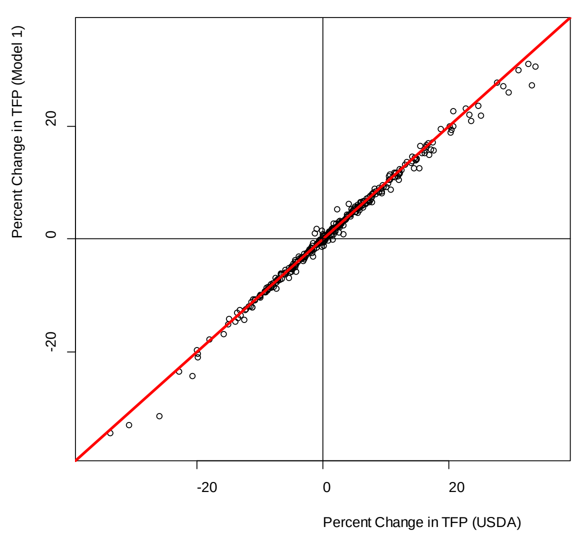


Panel a. Adjusted Technical Change estimates from Model 2

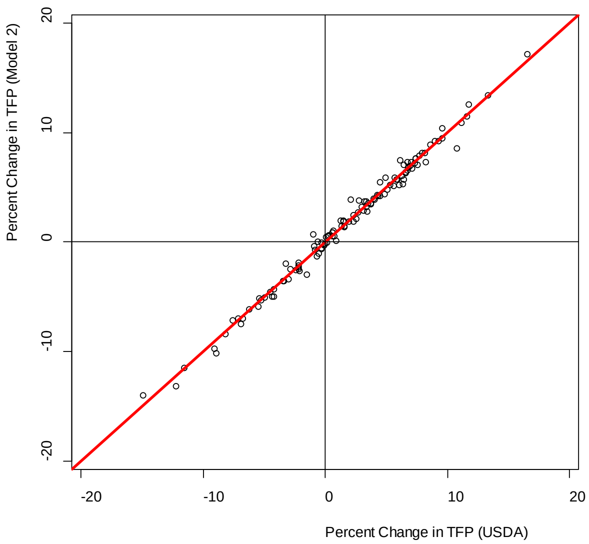
Figure 1. Annual Median Technical Change Estimates, $\frac{C_v(w_v,X_v)}{C_o(w,X)}\widehat{TC}$, for California and Iowa, 1964-2004.



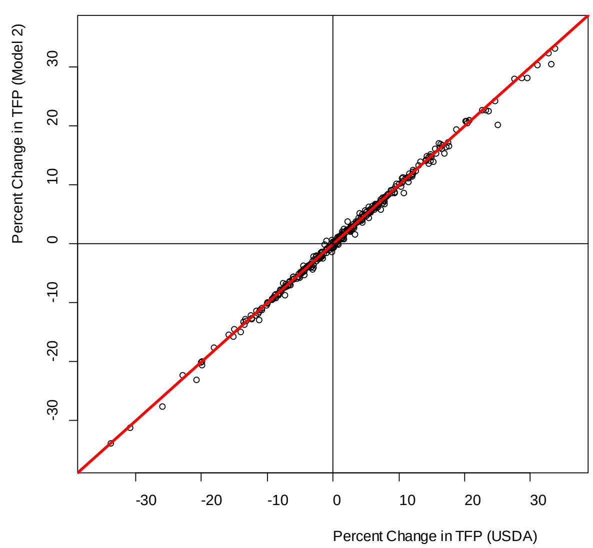
Panel a. $T\dot{F}P$ in Pacific Region: USDA vs. Model 1



Panel b. $T\dot{F}P$ in Central Region: USDA vs. Model 1

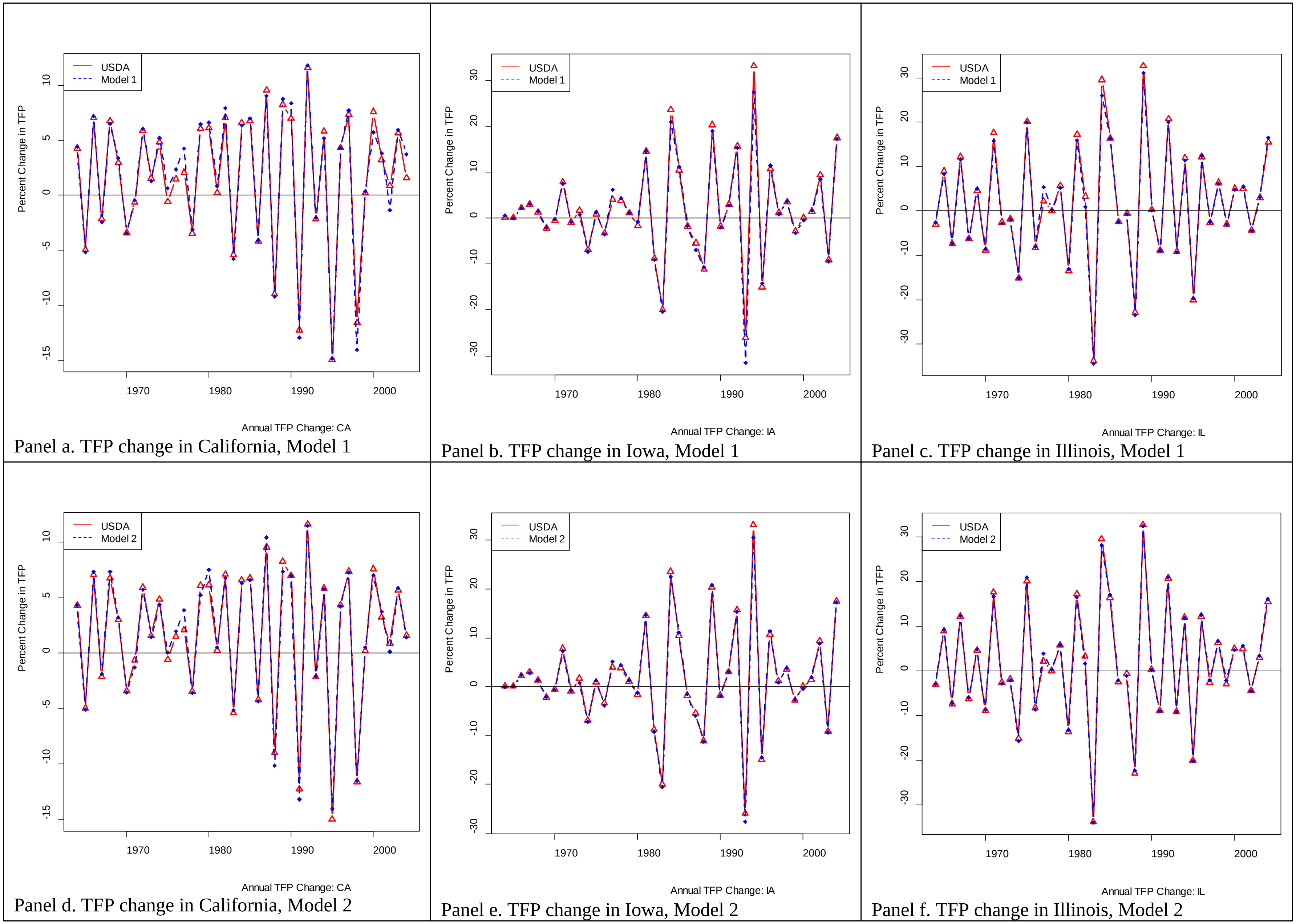


Panel c. $T\dot{F}P$ in Pacific Region: USDA vs. Model 2



Panel d. $T\dot{F}P$ in Central Region: USDA vs. Model 2

Figure 1. $T\dot{F}P$ estimates: USDA vs. Ours



Panel a. TFP change in California, Model 1

Panel b. TFP change in Iowa, Model 1

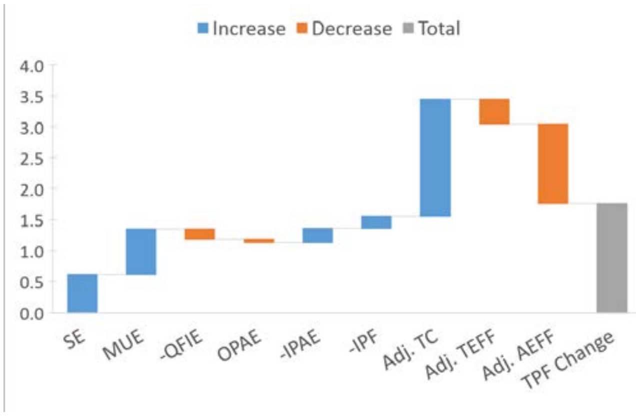
Panel c. TFP change in Illinois, Model 1

Panel d. TFP change in California, Model 2

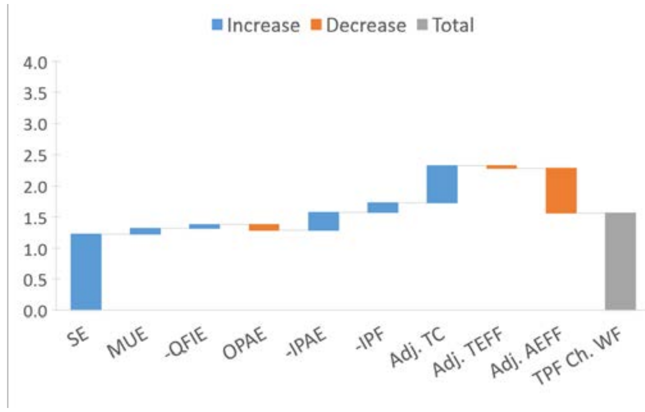
Panel e. TFP change in Iowa, Model 2

Panel f. TFP change in Illinois, Model 2

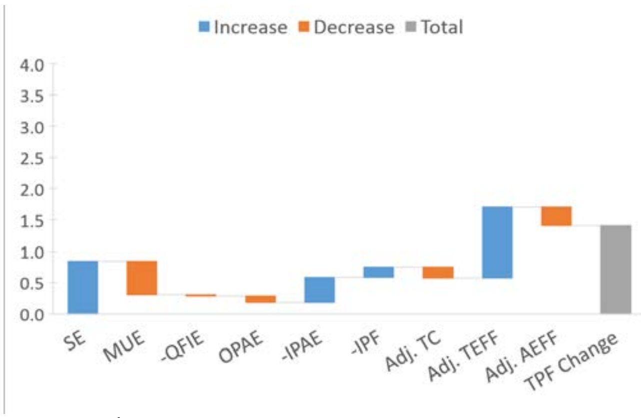
Figure 2. Annual $\dot{TFP}$ for selected states



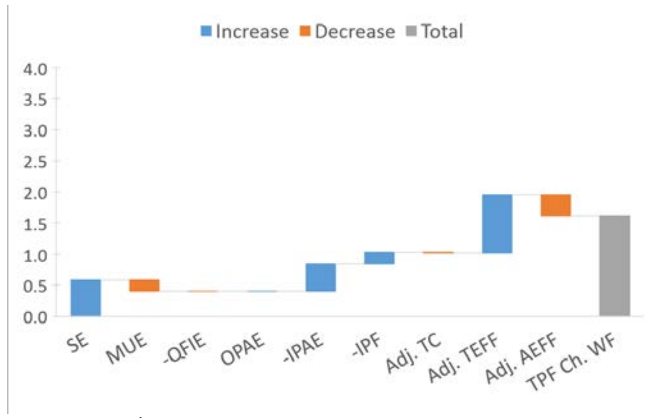
Panel a. $T\dot{F}P$ in California, Model 1



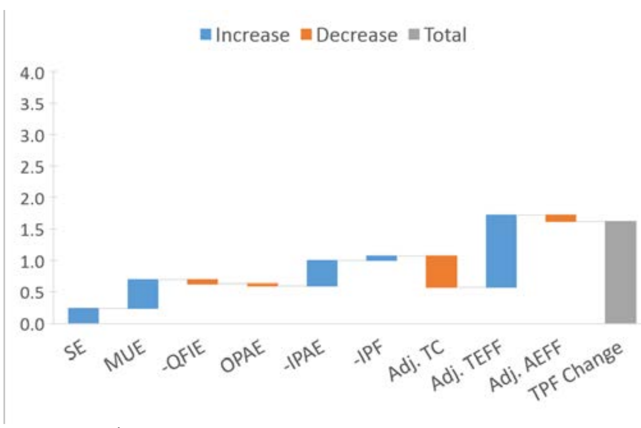
Panel b. $TF\dot{P}^{WF}$ in California, Model 2



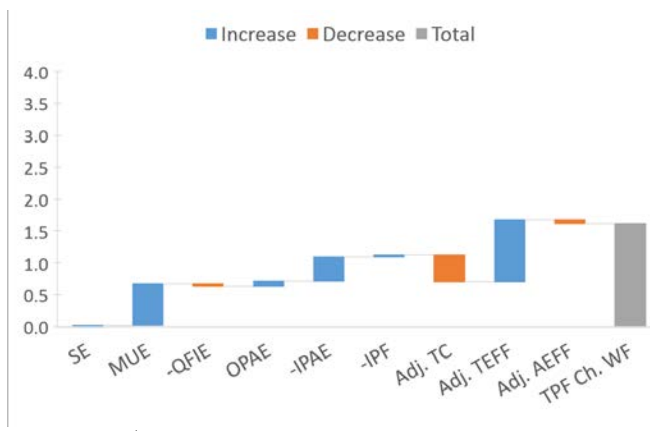
Panel c. $T\dot{F}P$ in Iowa, Model 1



Panel d. $TF\dot{P}^{WF}$ in Iowa, Model 2



Panel e. $T\dot{F}P$ in Illinois, Model 1



Panel f. $TF\dot{P}^{WF}$ in Illinois, Model 2

Figure 3. Average contribution of each component to $T\dot{F}P$ and $TF\dot{P}^{WF}$ for selected states, by Model