How Weather Affects the Decomposition of Total Factor Productivity in U.S. Agriculture

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Abstract

Despite the major role of climate in agricultural production, few studies have analyzed how weather fluctuations affect the measurement and decomposition of Total Factor Productivity (TFP). This article proposes a novel framework to decompose TFP change accounting for the influence of weather. Specifically, we estimate the contribution of weather variations, technical change, technical and allocative efficiency, as well as markup, scale and price effects to TFP change. The underlying technology is represented by a multi-input, multi-output flexible input distance function with quasi-fixed inputs of production, and is estimated for major U.S. producing regions using Bayesian methods. To assess the role of weather in the decomposition of TFP growth, we contrast findings from our proposed method with those of a baseline model that ignores weather effects. Overall, our TFP growth estimates are highly similar to those obtained from official USDA indices. However, we find that the contribution of non-weather components to TFP is 14% *lower* when we account for weather variations. This weather-related bias is particularly strong in the Central region of the country. This overestimation of TFP growth that is attributable to non-weather components in previous research thus implies that estimated rates of return to public R&D are also overestimated, which has profound policy implications. This is the first study to document how ignoring weather can bias the decomposition of TFP change estimates.

Key Words: Agricultural productivity, allocative efficiency, Bayesian methods, markup, price aggregation effect, quasi-fixed input, scale effect, technical change, technical efficiency, total factor productivity, weather.

JEL Codes: C11, D24, O47, Q18

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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 three 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. 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). Sabasi and Shumway (2018), evaluate the impact of climate change (based on 30-year moving averages of temperature and precipitation) and weather (current year precipitation and damaging degree days) on O'Donnell's (2012) series of TFP change, technical change, technical efficiency change and scale and mix efficiency change. They find that climate change not only had positive but also the largest impact on each of the four series among 16 variables;[1] while current year precipitation and damaging degree days had, respectively, positive and negative impacts on each of the series.

The objective of this article is twofold. 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 Region the Pacific Region, and the Southern Plains over 1964-2004. Second, we assess the bias in the estimated individual contributions of each of the components of TFP change when failing to account for weather shocks, by comparing the estimates from a TFP change model that accounts for weather shocks with a baseline model that does not.

The present article provides further evidence of the sensitivity of agricultural productivity to weather variability (Ortiz-Bobea, Knippenberg, and Chambers 2018; Sabasi and Shumway 2018) and suggests that the official USDA's measures of TFP change have typically overestimated the rate of productivity growth in U.S. agriculture due to non-weather related (market or policy-driven) events. Our results shed light on the contribution of "weather-filtered" components to TFP change and the biases induced by failing to account for weather shocks in the estimation of those components.

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 change on weather-filtered production variables following an expanded version of the algorithm developed by Plastina and Lence (2018). In other words, our approach performs a TFP change decomposition based on projected input and output quantities in the absence of weather shocks.

Methodological Framework

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 simplify notation, 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,[2] $C_o(w, X) = \sum_i w_{v_i} X_{v_i} + \sum_g w_{q_g} X_{q_g}$ is the observed cost of production, X_v denotes variable inputs, and X_q represents quasi-fixed inputs (i.e., inputs that adjust very slowly to market or weather shocks).

Following Farrell (1957), we 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:

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

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:

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

$$\frac{\partial \ln C(\underline{Y}, w_v; X_q; t)}{\partial t} - \sum_i \frac{w_{v_i} X_{v_i}}{C_v(w_v, X_v)} \left(\dot{w}_{v_i} + \dot{X}_{v_i}\right),$$

Upon rearrangement, by replacing the last term of (4) into (2), TFP change can be expressed as:

$$(5)\ \dot{TFP} = \dot{Y} - \sum_g s_{q_g} \left(\dot{w}_{q_g} + \dot{X}_{q_g}\right) + \dot{W} + \frac{C_v(w_v, X_v)}{C_o(w, X)} \Big\{TC + \dot{TE} + \dot{AE} -$$

$$\sum_n \varepsilon_{CY_n}\left(\underline{Y}, w_v; X_q; t\right) \dot{Y}_n - \sum_g \varepsilon_{CX_{q_g}}\left(\underline{Y}, w_v; X_q; t\right) \dot{X}_{q_g} - \sum_i s^*_{v_i}\left(\underline{Y}, w_v; X_q; t\right) \dot{w}_{v_i}\Big\},$$

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; $s^*_{v_i}\left(\underline{Y}, w_v; X_q; t\right) \equiv \frac{\partial \ln C(\underline{Y}, w_v; X_q; t)}{\partial \ln w_{v_i}}$ 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; $\varepsilon_{CY_n}\left(\underline{Y}, w_v; X_q; t\right) \equiv \frac{\partial \ln C(\underline{Y}, w_v; X_q; t)}{\partial \ln Y_n}$ is the cost elasticity with respect to output Y_n; and $\varepsilon_{CX_{q_g}}\left(\underline{Y}, w_v; X_q; t\right) \equiv \frac{\partial \ln C(\underline{Y}, w_v; X_q; t)}{\partial \ln X_{q_g}}$ 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:

$$(6)\ \dot{TFP} = \left(\dot{Y}_R - \frac{C_v(w_v, X_v)}{C_o(w, X)} \dot{Y}_C\right) + \frac{C_v(w_v, X_v)}{C_o(w, X)} (1 - RTS^{-1})\, \dot{Y}_C - \sum_g \Big\{s_{q_g} +$$

$$\frac{C_v(w_v, X_v)}{C_o(w, X)} \varepsilon_{CX_{q_g}}\left(\underline{Y}, w_v; X_q; t\right)\Big\} \dot{X}_{q_g} - \frac{C_v(w_v, X_v)}{C_o(w, X)} \sum_i \left\{s^*_{v_i}\left(\underline{Y}, w_v; X_q; t\right) - s_{v_i}\right\} \dot{w}_{v_i} +$$

$$\left(\sum_n R_n \dot{p}_n - \dot{P}\right) - \Big\{\sum_i \frac{w_{v_i} X_{v_i}}{C_o(w, X)} \dot{w}_{v_i} - \sum_g \frac{w_{q_g} X_{q_g}}{C_o(w, X)} \dot{w}_{q_g} - \dot{W}\Big\} + \frac{C_v(w_v, X_v)}{C_o(w, X)} \left\{TC + \dot{TE} + \dot{AE}\right\},$$

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

Equations (6) and (7) collapse to the expression described by Bauer (1990), and applied by Plastina and Lence (2018), 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 $p_n = \frac{C_v(w_v,X_v)}{C_o(w,X)}\frac{\partial C_v(\underline{Y},w_v;X_q;t)}{\partial Y_n}$ and $R_n = \frac{C_v(w_v,X_v)}{C_o(w,X)}\varepsilon_{CY_n}(\underline{Y},w_v;X_q;t)$, 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 short-term productivity changes stemming from changes in the scale of production.[3] The term $QFIE \equiv \sum_g \left\{s_{q_g} + \frac{C_v(w_v,X_v)}{C_o(w,X)}\varepsilon_{CX_{q_g}}(\underline{Y},w_v;X_q;t)\right\}\dot{X}_{q_g}$ is the quasi-fixed inputs effect, measured as the sum of net impacts of direct effects on observed total cost and indirect effects on minimum costs from changes in the levels of the quasi-fixed inputs. The term $IPF \equiv \frac{C_v(w_v,X_v)}{C_o(w,X)}\sum_i\{s_{v_i}^*(\underline{Y},w_v;X_q;t) - s_{v_i}\}\dot{w}_{v_i}$ 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 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, $OPAE \equiv (\sum_n R_n\dot{p}_n - \dot{P})$, 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 and quasi-fixed inputs constant.[4] 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 $Y^e \equiv \sum_n p_n^e Y_n^e / P^e$ 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 $\eta \equiv \frac{X}{X^e} \geq 0$ (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 $\eta < (>)\ 1$, 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, $\dot{\eta}$: $\dot{X} \equiv \dot{X}^e + \dot{\eta}$. Defining the net weather effect on TFP change as $NWEFF \equiv (\dot{\gamma} - \dot{\eta})$, the weather-filtered TFP change, $T\dot{FP}^{WF}$, can be calculated as:

$$(8)\ T\dot{FP}^{WF} = T\dot{FP} - NWEFF$$

$$= MUE^e + SE^e - QFIE^e - IPF^e + OPAE^e - IPAE^e + \frac{C_v^e(w_v^e, X_v^e)}{C_O^e(w^e, X^e)}\{TC^e + T\dot{E}^e + A\dot{E}^e\}.$$

The interpretation of $NWEFF$ admits two variants. The first one is that, for a given level of $T\dot{FP}^{WF}$, weather shocks foster (hinder) TFP change when $NWEFF > (<)\ 0$. The second one stems from the traditional use of non-weather filtered productivity measures. A positive (negative) net weather effect (i.e., $NWEFF > (<)\ 0$) is a confounding factor that leads to an overestimation (underestimation) of the actual growth of weather-filtered TFP change, and therefore of the portion of productivity change that reacts to changes in market conditions and public policies; in turn, this is equivalent to underestimating (overestimating) production risks from weather shocks.

Econometric Model to Estimate Agricultural Technology

Two models are estimated using an input distance function to represent the underlying agricultural technology (Plastina and Lence 2018).[5] Models 1 and 2 are estimated, respectively, using the original USDA production variables, and our weather-filtered variables. Estimates of TFP change and net weather effects on TFP change are later derived using parameter estimates from Models 1 and 2, and equations (6)-(8). For simplicity, the econometric estimation approach is only discussed in terms of Model 1, but it applies *pari passu* to the estimation of Model 2. For each region, the estimated model consists of the following translog approximation to the input distance function $D(\underline{Y}, X; t)$:

(9) $-x_{v_1st} = \beta_0 + \sum_{n=1}^{N} \alpha_n \, y_{nst} + \sum_{i=2}^{I} \beta_{v_i} \, \tilde{x}_{v_ist} + \sum_{g=1}^{G} \beta_{q_g} \, x_{q_gst} +$

$\frac{1}{2}\sum_{m=1}^{N}\sum_{n=1}^{N} \alpha_{mn} \, y_{mst} \, y_{nst} + \frac{1}{2}\sum_{i=2}^{I}\sum_{j=2}^{I} \beta_{v_iv_j} \, \tilde{x}_{v_ist} \, \tilde{x}_{v_jst} +$

$\frac{1}{2}\sum_{g=1}^{G}\sum_{h=1}^{G} \beta_{q_gq_h} \, x_{q_gst}x_{q_hst} + \frac{1}{2}\sum_{g=1}^{G}\sum_{i=2}^{I} \beta_{q_gv_i} \, x_{q_gst}\tilde{x}_{v_ist} +$

$\sum_{n=1}^{N}\sum_{i=2}^{I} \delta_{nv_i} \, y_{nst} \, \tilde{x}_{v_ist} + \sum_{n=1}^{N}\sum_{g=1}^{G} \delta_{nq_g} \, y_{nst} \, x_{q_gst} + \sum_{t=1}^{T} \lambda_t d_t \Big[1 +$

$\sum_{n=1}^{N} \alpha_{n\Theta} \, y_{nst} + \sum_{i=2}^{I} \beta_{v_i\Theta} \, \tilde{x}_{v_ist} + \sum_{g=1}^{G} \beta_{q_g\Theta} \, x_{q_gst}\Big] - \left(\rho_{0s} + \rho_{1s}t + \frac{1}{2}\rho_{2s}t^2\right) + \vartheta_{st},$

where $x_{v_1st} \equiv \ln X_{v_1st}$ is the logarithm of the numeraire (variable) input, $y_{nst} \equiv \ln Y_{nst}$ is the logarithm of the *n*-th output, $x_{q_gst} \equiv \ln X_{q_gst}$ is the logarithm of the *g*-th quasi-fixed input, $\tilde{x}_{v_ist} \equiv \ln\left(\frac{X_{v_ist}}{X_{v_1st}}\right)$ 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 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.

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

(11) $\sum_{i=1}^{I} \beta_{v_iv_j} = \sum_{i=1}^{I} \beta_{q_gv_i} = \sum_{i=1}^{I} \delta_{nv_i} = \sum_{i=1}^{I} \beta_{v_i\Theta} = 0;$

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

(12) $\frac{\partial \ln D(Y,X;t)}{\partial y_{mst}} = \alpha_m + \sum_n \alpha_{mn}y_{nst} + \sum_{i=1}^{I} \delta_{mv_i}x_{v_ist} + \sum_{g=1}^{G} \delta_{mq_g}x_{q_gst} + \lambda_t\alpha_{m\Theta} \le 0;$

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

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

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

$0;$

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

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

e) concave in variable inputs, i.e.

(16) $\begin{bmatrix} \beta_{v_1 v_1} & \cdots & \beta_{v_1 v_I} \\ \vdots & \ddots & \vdots \\ \beta_{v_I v_1} & \cdots & \beta_{v_I v_I} \end{bmatrix}$ 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 equations for each of the $(I-1)$ input ratios and the G quasi-fixed inputs:

(17) $\tilde{x}_{v_j st} = \zeta_0^{v_j} + \sum_{n=1}^{N} \varphi_n^{v_j} y_{nst} + \sum_{i=1}^{I} \zeta_i^{v_j} \ln w_{v_i st} + \sum_{g=1}^{G} \zeta_g^{v_j} \ln w_{q_g st} +$

$\frac{1}{2} \sum_{m=1}^{N} \sum_{n=1}^{N} \varphi_{mn}^{v_j} y_{mst} y_{nst} + \frac{1}{2} \sum_{i=1}^{I} \sum_{g=1}^{G} \zeta_{i q_g}^{v_j} \ln w_{v_i st} \ln w_{q_g st} +$

$\sum_{n=1}^{N} \sum_{i=1}^{I} \varsigma_{n v_i}^{v_j} y_{nst} \ln w_{v_i st} + \sum_{n=1}^{N} \sum_{g=1}^{G} \varsigma_{n q_g}^{v_j} y_{nst} \ln w_{q_g st} + \vartheta_{st}^{v_j}, j = 2, \ldots, I,$

(18) $x_{q_h st} = \zeta_0^{q_h} + \sum_{n=1}^{N} \varphi_n^{q_h} y_{nst} + \sum_{i=1}^{I} \zeta_i^{q_h} \ln w_{v_i st} + \sum_{g=1}^{G} \zeta_g^{q_h} \ln w_{q_g st} +$

$\frac{1}{2} \sum_{m=1}^{N} \sum_{n=1}^{N} \varphi_{mn}^{q_h} y_{mst} y_{nst} + \frac{1}{2} \sum_{i=1}^{I} \sum_{g=1}^{G} \zeta_{ig}^{q_h} \ln w_{v_i st} \ln w_{q_g st} +$

$\sum_{n=1}^{N} \sum_{i=1}^{I} \varsigma_{ni}^{q_h} y_{nst} \ln w_{v_i st} + \sum_{n=1}^{N} \sum_{g=1}^{G} \varsigma_{n q_g}^{q_h} y_{nst} \ln w_{q_g st} + \vartheta_{st}^{q_h}, h = 1, \ldots, G,$

and simultaneously estimate (9) and (17)-(18) 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 (17)-(18) 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):

$$(19) \quad \min_{[\hat{\tilde{x}}_{v_2 st},\dots,\hat{\tilde{x}}_{v_I st}]} w_{1st}\, e^{-\hat{p}_{st}-\hat{q}(\hat{\tilde{x}}_{v_2 st},\dots,\hat{\tilde{x}}_{v_I st})}\left(1+\sum_{i=2}^{I}\frac{w_{v_i st}}{w_{v_1 st}}\, e^{\hat{\tilde{x}}_{v_i st}}\right),$$

where a hat over a variable indicates its fitted value, $\hat{X}_{v_1 st} = e^{\hat{x}_{v_1 st}}$, $\hat{X}_{v_i st}/\hat{X}_{v_1 st} = e^{\hat{\tilde{x}}_{v_i st}}$, $\hat{p}_{st} \equiv \hat{\beta}_0 + \sum_{n=1}^{N}\hat{\alpha}_n\, y_{nst} + \sum_{g=1}^{G}\hat{\beta}_{q_g}\, x_{q_g st} + \frac{1}{2}\sum_{m=1}^{N}\sum_{n=1}^{N}\hat{\alpha}_{mn}\, y_{mst}\, y_{nst} + \frac{1}{2}\sum_{g=1}^{G}\sum_{h=1}^{G}\hat{\beta}_{q_g q_h}\, x_{q_g st} x_{q_h st} + \sum_{n=1}^{N}\sum_{g=1}^{G}\hat{\delta}_{n q_g}\, y_{nst}\, x_{q_g st} + \sum_{t=1}^{T}\hat{\lambda}_t d_t\left[1+\sum_{n=1}^{N}\hat{\alpha}_{n\Theta}\, y_{nst} + \sum_{g=1}^{G}\hat{\beta}_{q_g\Theta}\, x_{q_g st}\right] - \min\{\hat{u}_{st}\}$, and $\hat{q}(\hat{\tilde{x}}_{v_2 st},\dots,\hat{\tilde{x}}_{v_I st}) \equiv \sum_{i=2}^{I}\hat{\beta}_{v_i}\,\hat{\tilde{x}}_{v_i st} + \frac{1}{2}\sum_{i=2}^{I}\sum_{j=2}^{I}\hat{\beta}_{v_i v_j}\,\hat{\tilde{x}}_{v_i st}\,\hat{\tilde{x}}_{v_j st} + \sum_{n=1}^{N}\sum_{i=2}^{I}\hat{\delta}_{n v_i}\, y_{nst}\,\hat{\tilde{x}}_{v_i st} + \frac{1}{2}\sum_{g=1}^{G}\sum_{i=2}^{I}\hat{\beta}_{q_g v_i}\, x_{q_g st}\hat{\tilde{x}}_{v_i st} + \sum_{t=1}^{T}\hat{\lambda}_t d_t \sum_{i=2}^{I}\hat{\beta}_{v_i\Theta}\,\hat{\tilde{x}}_{v_i st}$. The solution to the unconstrained optimization (19) yields the estimated minimum cost $\hat{C}(\underline{Y}_{st}, w_{vst}; X_{qst}; t)$ and the vector of optimal variable input ratio estimates $[\hat{\tilde{x}}^{*}_{v_2 st},\dots,\hat{\tilde{x}}^{*}_{v_I st}]$. The input price factor is then calculated as

$$(20) \quad \widehat{IPF} = \frac{C_v(w_v,X_v)}{C_o(w,X)}\sum_i\left\{\hat{s}^{*}_{v_i}(\underline{Y}, w_v; X_q; t) - s_{v_i}\right\}\dot{w}_{v_i} = \frac{C_v(w_v,X_v)}{C_o(w,X)}\sum_i\left\{\frac{w_{v_i st}\,\hat{X}^{*}_{v_i st}}{\sum_{i=1}^{I} w_{v_i st}\,\hat{X}^{*}_{v_i st}} - s_{v_i}\right\}\dot{w}_{v_i},$$

where $\hat{s}^{*}_{v_i}(\underline{Y}, w_v; X_q; t) \equiv w_{v_i st}\,\hat{X}^{*}_{v_i st}/(\sum_{i=1}^{I} w_{v_i st}\,\hat{X}^{*}_{v_i st})$ is the estimated cost-minimizing *i*-th variable input share, and $\hat{X}^{*}_{v_i st}$ is the estimated cost-minimizing level of the *i*-th variable input, which is recovered as[6]

$$(21) \quad \hat{X}^{*}_{v_i st} = e^{-\hat{p}_{st}-\hat{q}(\hat{\tilde{x}}^{*}_{v_2 st},\dots,\hat{\tilde{x}}^{*}_{v_I st})+\hat{\tilde{x}}^{*}_{v_i st}}, i = 1,\dots,I.$$

Recovering Allocative Efficiency Change

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

$$(22)\quad \widehat{\dot{AE}}_{st} = -\widehat{\dot{TE}}_{st} + \left[\ln \hat{C}\left(\underline{Y}_{st}, w_{vst}; X_{qst}; t\right) - \ln \hat{C}\left(\underline{Y}_{st-1}, w_{vst-1}; X_{qst-1}; t-1\right)\right] - [\ln C_v(w_{st}, X_{vst}; t) - \ln C_v(w_{st-1}, X_{vst-1}; t-1)].$$

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 (19) 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 $TC \equiv -\frac{\partial \ln C(\underline{Y}, w_v; X_q; t)}{\partial t}$, here it is estimated as

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

The minimum costs involved in this expression are computed by solving the cost-minimization problem (19) for state s, keeping variable input prices, quasi-fixed input quantities, and output 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

$$(24)\quad \hat{\varepsilon}_{CY_n}\left(\underline{Y}_{st}; w_{vst}; X_{qst}; t\right) = \frac{\ln \hat{C}\left(1.01\times \underline{Y}_{n,st}; \underline{Y}_{l\neq n,st}; w_{vst}; X_{qst}; t\right) - \ln \hat{C}\left(\underline{Y}_{st}; w_{vst}; X_{qst}; t\right)}{\ln\left(1.01\times \underline{Y}_{n,st}\right) - \ln \underline{Y}_{n,st}}, \text{ and}$$

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

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 TFP -weather model developed by Ortiz-Bobea, Knippenberg, and Chambers (2018). We use a spline with three equally-spaced knots to model the nonlinear effects of exposure to various temperature levels and a quadratic specification to model precipitation. For each variable, we conduct a grid search based on a 10-fold cross-validation over all possible calendar time windows to identify the "optimal" season. The optimal season corresponds to the calendar period that provides the best out-of-sample prediction accuracy for a given predictand. 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 (average weather conditions over the sample period).

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 $\hat{X}^e \equiv$

$(\sum_i \widehat{w}^e_{v_i}\hat{X}^e_{v_i} + \sum_g \widehat{w}^e_{q_g}\hat{X}^e_{q_g})/\widehat{W}^e$. The resulting estimates are in turn used to compute the abnormal weather output and input effects, $\hat{\dot{\gamma}}_n = \dot{Y}_n - \hat{\dot{Y}}^e_n$, and $\hat{\dot{\eta}}_j = \dot{X}_j - \hat{\dot{X}}^e_j$, respectively, and $TF\dot{P}^{WF}$.[7]

Data

In order to highlight the varying effects of weather shocks across different regions, we focus on three regions: the Pacific Region (California, Oregon, Washington), the Central Region (Iowa, Illinois, Indiana, Michigan, Missouri, Minnesota, Ohio, and Wisconsin), and the Southern Plains (Arkansas, Louisiana, Mississippi, Oklahoma, and Texas). 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 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 $X_q = \{A\}$.[9]

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 (9), (17)-(18). Bayesian techniques are quite advantageous for the present article, because they greatly facilitate imposing the desired monotonicity and concavity restrictions in estimation (i.e., (10)-(16)), and performing the corresponding inferences (e.g., O'Donnell and Coelli (2005) and Plastina and Lence (2018, 2019)). It would be quite difficult, if not impossible, to impose restrictions (13)-(16) 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 weather-filtered 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.[10]

Estimation of the models 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 $\{\alpha, \beta, \delta, \lambda, \rho, \zeta, \varphi, \varsigma\}$ of the system of equations (9), (17)-(18), the priors are Student-*t*[3, 0, max(5, >15×PostStDev$_i$)], i.e., Student's *t* distributions with 3 degrees of freedom, 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.[11] The covariance matrix of residuals ϑ_{st}, $\vartheta_{st}^{v_j}$, and $\vartheta_{st}^{q_h}$ is computed as the product

$$(26)\quad \begin{bmatrix} \sigma_{\vartheta}^2 & \sigma_{\vartheta\vartheta^{v_2}} & \sigma_{\vartheta\vartheta^{v_3}} & \sigma_{\vartheta\vartheta^{q_1}} \\ \sigma_{\vartheta\vartheta^{v_2}} & \sigma_{\vartheta^{v_2}}^2 & \sigma_{\vartheta^{v_2}\vartheta^{v_3}} & \sigma_{\vartheta^{v_2}\vartheta^{q_1}} \\ \sigma_{\vartheta\vartheta^{v_3}} & \sigma_{\vartheta^{v_2}\vartheta^{v_3}} & \sigma_{\vartheta^{v_3}}^2 & \sigma_{\vartheta^{v_3}\vartheta^{q_1}} \\ \sigma_{\vartheta\vartheta^{q_1}} & \sigma_{\vartheta^{v_2}\vartheta^{q_1}} & \sigma_{\vartheta^{v_3}\vartheta^{q_1}} & \sigma_{\vartheta^{q_1}}^2 \end{bmatrix} = \sigma\Lambda\Lambda^{\mathrm{T}}\sigma^{\mathrm{T}},$$

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 half 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 (26). That is, we estimate it as the product

$$(27)\quad \begin{bmatrix} \alpha_{HH} & \alpha_{HV} & \alpha_{HO} \\ \alpha_{HO} & \alpha_{VV} & \alpha_{VO} \\ \alpha_{HO} & \alpha_{VO} & \alpha_{OO} \end{bmatrix} = \Phi\Upsilon\Upsilon^{\mathrm{T}}\Phi^{\mathrm{T}},$$

where Φ is a (3×3) diagonal matrix, and Υ is the Cholesky factor of a (3×3) correlation matrix. The prior for $\Phi_{ii}^2 \geq 0$ is half Student-*t*[3, 0, max(5, >15×PostStDev$_i$)], whereas the prior for 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 (27) 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 (16) 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 (11). Therefore, the symmetric matrix with coefficients $\{\beta_{KK}, \beta_{KL}, \beta_{LL}\}$ is first computed as the negative of a covariance matrix.[12] 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 the set of coefficients $\{\beta_{KK}, \beta_{KL}, \beta_{LL}, \beta_{MM}, \beta_{KM}, \beta_{LM}\}$ satisfies 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 (12) is imposed by estimating the α_m coefficients in regression (9) as

$$(28)\quad \alpha_m = -\psi_m^2 - \max_{s,t}\left[\sum_{n\in\{H,V,O\}} \alpha_{mn}\, y_{nst} + \sum_{j\in\{K,L\}} \delta_{mj}\, \tilde{x}_{jst} + \delta_{mA}\, x_{Ast} + \lambda_t \alpha_{m\Theta}\right],$$

for $m \in \{H, V, O\}$, with a half-Student-*t*[3, 0, max(5, >15×PostStDev$_m$)] prior for parameter $\Phi_m^2 \geq 0$.

The method used to impose conditions (13)-(14), i.e., that the distance function be non-decreasing in inputs, is analogous to the one underlying expression (28), so that

$$(29)\quad \beta_{v_j} = \psi_{v_j}^2 - \min_{s,t}\left[\sum_{i\in\{K,L\}} \beta_{v_i v_j}\, \tilde{x}_{v_i st} + \beta_{v_j A} x_{Ast} + \sum_{n\in\{H,V,O\}} \delta_{n v_j}\, y_{nst} + \lambda_t \beta_{v_j \Theta}\right], j \in \{K, L\},$$

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

with half-Student-*t*[3, 0, max(5, >15×PostStDev$_j$)] priors for parameters $\psi_{v_j}^2 \geq 0$ and $\psi_A^2 \geq 0$. But due to the fact that the coefficient for the materials input β_M is recovered after estimation from the homogeneity constraint (10) (i.e., $\beta_M = 1 - \beta_K - \beta_L$) rather than estimated directly, condition (13) 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. To enhance the efficiency of the sampler and facilitate convergence, the logarithms of original variables were standardized by subtracting the mean and dividing them by the absolute standard deviation before the estimation (Stan Development Team 2019).[13] For the same reasons, the variables associated with the unrestricted coefficients $\{\alpha, \beta, \delta, \lambda, \rho, \zeta, \varphi, \varsigma\}$ were reparameterized in terms of their principal components for estimation purposes.[14]

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 parameters.

Results and Discussion

For simplicity of exposition, we first focus on the estimated effects of abnormal weather on TFP change by state 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 shocks). 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 shocks are not accounted for. This is the first article to measure those biases in U.S. agriculture.

Estimated Effects of Weather Shocks

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 weather shocks 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 ($\hat{\hat{\gamma}}$) were larger in absolute values than mean weather effects on input change ($\hat{\hat{\eta}}$) for all states in the sample except for Minnesota (where both effects are close in absolute value) and Oklahoma.[15] Illinois, Indiana, Michigan, and Ohio in the Central Region and all states in the Southern Plains experienced, on average, productivity-enhancing weather shocks 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 weather shocks to outputs dominated the productivity-reducing weather shocks on inputs. In contrast, for Oregon, Washington, and Wisconsin, on average the productivity-reducing weather shocks on outputs dominated the productivity-enhancing weather shocks on inputs. Finally, Minnesota experienced productivity-reducing weather shocks on both outputs and inputs.

On average, net weather effects on TFP change ($\widehat{NWEFF} = \hat{\hat{\gamma}} - \hat{\hat{\eta}}$) were positive across the 16 states in the sample (averaging 0.10 percentage points of TFP change). However, while weather shocks had negative average net effects on TFP change in the Pacific Region (averaging -0.0369 percentage points), they had average positive net effects in the Central Region and the Southern Plains (averaging, respectively, 0.1135 and 0.1607 percentage points). Overall, weather shocks played a larger role in explaining output changes than input changes in the three regions, although with great heterogeneity across states. 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. However, while our results point to average positive effects of weather shocks on TFP growth Njuki, Bravo-Ureta, and O'Donnell (2018) conclude that climatic effects slowed down TFP growth across the 48 continental states of the United States by an average -0.012 percentage points over 1960-2004.

Parameter Estimates from the Distance Function

Tables 4a and 4b 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. 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 all regions, at least one estimated cross-equation correlation between ϑ_{st} and ϑ_{st}^{K} , ϑ_{st}^{L}, or ϑ_{st}^{A} is positive and significant (its corresponding 95% CIs exclude the null value), suggesting that the system-of-equations approach followed in this article is superior to the alternative single-equation approach.

Scale Effect, $\widehat{SE}$

According to Model 2 estimates, all states have benefited from changing their scale of production (table 5). The estimated annual contribution of the scale effect to weather-filtered TFP change from Model 2 averaged 1.51% in the Pacific Region, 0.50% in the Central Region, and 0.80% in the Southern Plains. However, annual estimates varied substantially, ranging from -23.50% (Mississippi, 1993) to 20.24% (Mississippi, 2003). 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, 0.53 percentage points for the Central Region, and 0.43 percentage points for the Southern Plains, 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 (-0.05%) across all states in the sample (Model 2 in table 6). Only Mississippi, Illinois, and Arkansas benefited substantially from non-marginal pricing, adding an average 0.88%, 0.66%, 0.56% to weather-filtered TFP change over 1964-2004. Oklahoma experienced the largest negative markup effects, averaging -1.12% over the same period, followed by Louisiana (-0.62%), Oregon (-0.40%), Wisconsin (-0.37%), Minnesota (-0.35%), and Washington (-0.33%). It is important to note that the bias introduced by failing to account for weather effects (Model 1 in table 6) is substantial: 0.84 percentage points in the Pacific Region, -0.49 percentage points in the Central Region, and -0.21 percentage points in the Southern Plains, 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 7. 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 7 that weather-adjusted technical change (Model 2) in the Pacific region has been the strongest at 0.67%, on average, over 1964-2004, followed by the Central region and the Southern Plains (-0.04% and -1.19%, respectively). Failing to account for weather effects induces upward biases in the estimates of adjusted technical change for the Pacific Region and the Southern Plains (averaging 1.10 and 0.62 percentage points, respectively), and downward biases in the Central Region (averaging -0.13 percent points). Negative technical change in this framework might reflect that changes in input mixes can be costly to implement (Lucas 1967, Caballero 1994, Hamermesh and Pfann 1996, Hall 2004, Lambert and Gong 2010; Yang and Shumway 2016).

Figure 1 illustrates the evolution of adjusted technical change for California, Iowa, and Texas, the top three agricultural producers in the sample (accounting, respectively, for 10.5% 6.7%, and 6.6% 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 and Texas. 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 in California drops by about two-thirds.

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 8. The average annual median estimate across all states and years in Model 2 is 1.78%, with median annual estimates ranging from -3.56% (Arkansas, 1964) to 6.49% (Louisiana, 2004). All states in the Central Region and the Southern Plains 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 states in the Pacific Region, 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 and the Southern Plains, with biases averaging 0.17%, -0.38%, and -0.75%, 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 9. The average annual median estimate across all states and years is -0.18% in Model 2, but the ranges of median annual estimates are quite wide, going from -21.29% (Mississippi, 1993) to 17.76% (Arkansas, 1975). All states but Oregon, Arkansas, Louisiana, and Mississippi 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%, -0.04%, and -0.16% for the Pacific Region, the Central Region, and the Southern Plains, 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 in the Pacific and Central Regions but Michigan (-0.15%), averaging 0.02% and -0.06%, respectively (Model 2 in table 10). However, in the Southern Plains, the impact is non-negligible, averaging -0.34% across states and years. 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 not negligible for the Pacific Region and the Southern Plains, averaging -0.04%, -0.22%, and 0.10%, 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 in the Pacific and Central Regions, except for Michigan (-0.15%) and Missouri (-0.13%), and averaging 0.18% and 0.12%, respectively (Model 2 in table 11). In the Southern Plains, the average $-\widehat{IPF}$ was negative for all states but Louisiana (0.02%), averaging -0.27%. The states that benefited the most from changes in observed input prices were Wisconsin, Minnesota, and Oregon, where weather-filtered TFP change increased by an average 0.60%, 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% across all states.

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 12 and 13, respectively. The average annual median $\widehat{OPAE}$ across all states and years is 0.05% on the weather-filtered variables (Model 2 in table 12). The average annual contribution of the input price aggregation effect to weather-filtered TFP change, i.e. $-\widehat{IPAE}$, amounted to 0.34% (Model 2 in table 13). 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, 0.21% in the Southern Plains, and 0.10% in the Pacific Region. The biases induced in the estimated output and input price aggregation effects by failing to account for weather effects (Model 1 in tables 12 and 13) are small in absolute value for most states, averaging -0.01%.

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 14. 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 0.11 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, and the Southern Plains are 0.991, 0.996, and 0.992 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, and the Southern Plains are 0.995, 0.998, and 0.992 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 Texas. 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 for the Pacific and Central Regions, and a slightly weaker goodness of fit for the Southern Plains.

From observation of tables 3, 5-14, 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 4 illustrates those biases for California, Iowa, and Texas.

By direct comparison of $\widehat{T\dot{F}P}^{WF}$ and $\widehat{T\dot{F}P}$ from Model 2 in table 14, it is apparent that in twelve out of the sixteen[16] states in our sample, agricultural productivity growth due to factors other than weather shocks was, on average, 0.17 percentage points slower than the estimated $\widehat{T\dot{F}P}$, and equivalent to 11.4% of the average $\widehat{T\dot{F}P}$ for those state. For the other four states[17] in our sample, all sitting in the northern most part of the country, agricultural productivity growth due to factors other than weather shocks was, on average, 0.11 percentage points higher than $\widehat{T\dot{F}P}$ (i.e., weather shocks reduced agricultural productivity by 6.5% of the average $\widehat{T\dot{F}P}$ in those states). This is the first article to provide a counterfactual analysis of the biases induced in TFP change estimates by failing to account for weather effects.

These findings call 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 $T\dot{F}P$, since the latter are, on average across all states in our sample, 0.21 percentage points higher than the former, and equivalent to 14% of the average rates of productivity growth reported by USDA).

Concluding comments

This article develops a novel analytical framework to estimate TFP change in the presence of quasi-fixed inputs of production and weather shocks. The underlying technology is represented by a flexible input distance function estimated using cutting-edge Bayesian methods. Using agricultural production data for the Pacific Region, the Central Region, and the Southern Plains of the U.S., TFP change is estimated as the direct sum of its components: weather shocks, 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 net effects of weather shocks 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 high degree of 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 article to present estimates of those biases based on a counterfactual analysis.

This article also 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 14% slower than the TFP change calculated from USDA's indexes over 1964-2004 for all states in the sample.[18]

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 production variables were 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.

Several caveats apply to the present article, 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. A future line of research is to explore the robustness of our results to modeling weather shocks (as defined in the present article) as exogenous and free inputs of production in the input distance function.

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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 1. Descriptive Statistics of the Original Variables (continued)

Variable	Unit	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
Southern Plains						
Aggregate Output quantity	thousand $ 1996	4,739,124	3,484,273	1,069,474	15,300,522	225
Aggregate Output price index	1 for AL 1996	0.774	0.263	0.340	1.316	225
Crops quantity	thousand $ 1996	1,972,624	1,302,513	492,525	5,966,374	225
Crops price index	1 for AL 1996	0.805	0.224	0.368	1.194	225
Livestock quantity	thousand $ 1996	2,396,648	1,890,320	531,035	7,941,664	225
Livestock price index	1 for AL 1996	0.767	0.315	0.280	1.575	225
Other Outputs quantity	thousand $ 1996	390,876	371,324	60,699	1,900,581	225
Other Outputs price index	1 for AL 1996	0.574	0.310	0.138	1.160	225
Aggregate Input quantity	thousand $ 1996	6,479,870	4,902,783	2,242,798	18,421,748	225
Aggregate Input price index	1 for AL 1996	0.621	0.321	0.138	1.211	225
Capital quantity	thousand $ 1996	823,375	614,056	287,255	2,548,731	225
Capital price index	1 for AL 1996	0.637	0.365	0.155	1.187	225
Labor quantity	thousand $ 1996	2,519,393	1,811,462	643,233	9,476,398	225
Labor price index	1 for AL 1996	0.390	0.276	0.049	1.246	225
Land quantity	thousand $ 1996	1,428,718	1,672,963	239,564	5,155,293	225
Land price index	1 for AL 1996	0.519	0.417	0.017	1.947	225
Materials quantity	thousand $ 1996	2,430,961	1,770,141	601,341	7,296,259	225
Materials price index	1 for AL 1996	0.813	0.344	0.299	1.447	225

Table 2. Best Fitting Model for Each Variable by Region

	Pacific Region				Central Region				Southern Plains			
	Start of the season (month)	End of the Season (month)	MSE Reduc-tion (%)	Correlation b/Observed and Model Estimate for all states in region	Start of the season (month)	End of the Season (month)	MSE Reduc-tion (%)	Correlation b/Observed and Model Estimate for all states in region	Start of the season (month)	End of the Season (month)	MSE Reduc-tion (%)	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	April	July	4	0.999
Crops quantity	February	April	12	0.999	April	September	46	0.989	July	December	17	0.998
Crops price index	May	August	0	0.988	April	July	13	0.970	April	November	11	0.997
Livestock quantity	August	August	1	1.000	March	March	5	0.999	January	March	1	0.993
Livestock price index	January	February	3	0.990	April	April	-1	0.986	October	October	5	1.000
Other Outputs quantity	January	May	12	0.996	September	September	3	0.980	January	March	9	0.998
Other Outputs price index	February	March	4	0.997	May	July	8	0.998	January	June	2	0.999
Aggregate Input price index	October	October	12	0.998	July	July	7	0.995	September	September	5	1.000
Capital quantity	February	February	5	1.000	January	June	6	1.000	December	December	4	1.000
Capital price index	July	October	10	0.999	October	November	3	0.999	June	September	-1	0.999
Labor quantity	May	June	7	0.996	February	March	1	0.994	May	May	6	1.000
Labor price index	February	June	7	0.992	January	February	2	0.982	October	December	2	1.000
Land quantity	June	December	12	1.000	September	September	6	1.000	January	March	2	1.000
Land price index	September	December	6	0.992	October	November	-1	0.992	August	August	-4	0.999
Materials quantity	April	July	-3	0.999	March	March	1	0.997	January	January	-3	1.000
Materials price index	October	October	2	0.996	May	September	13	0.991	September	September	16	0.997

Note: MSE = mean square error. The MSE reduction is computed in a 10-fold cross-validation exercise relative to a baseline model without weather variables.

Table 3. Estimated Weather Effects, 1964-2004 (in Percentage Points)

		Weather effect on output change, $\hat{\gamma}$				Weather effect on input change, $\hat{\eta}$				Net weather effect on TFP change, $\widehat{NEWFF} = \hat{\gamma}$-$\hat{\eta}$			
	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
Southern Plains													
AR	41	0.1113	5.21	-11.71	12.81	-0.0398	1.68	-3.46	3.11	0.1511	5.19	-10.23	12.81
LA	41	0.2135	4.87	-10.17	11.40	-0.0541	2.57	-5.33	5.89	0.2676	4.35	-6.05	10.11
MS	41	0.1624	4.72	-11.35	12.98	-0.0255	2.23	-4.44	4.29	0.1879	4.25	-8.13	11.66
OK	41	0.0040	5.34	-14.02	14.12	-0.1271	2.11	-6.53	2.81	0.1311	6.06	-16.76	19.04
TX	41	0.0338	3.75	-9.36	11.17	-0.0318	2.06	-3.30	5.10	0.0656	4.28	-8.06	11.08

Table 4a. Parameter Estimates from Input Distance Function, Pacific Region

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

Table 4b. 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 4c. Parameter Estimates from Input Distance Function, Southern Plains

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	-0.5886	-0.5787*	-0.8522	-0.8414*	δ_{VA}	-0.0212	-0.0178	-0.0179	-0.015
	(0.2083)	[-1.0306;-0.2054]	(0.2782)	[-1.4636;-0.3417]		(0.0257)	[-0.0806;0.0206]	(0.0255)	[-0.0745;0.0242]
α_V	-0.2463	-0.2361	-0.2829	-0.2679	δ_{OA}	-0.0035	-0.0028	-0.0088	-0.0077
	(0.2649)	[-0.7951;0.2614]	(0.2935)	[-0.9137;0.2658]		(0.0055)	[-0.0162;0.0053]	(0.0085)	[-0.028;0.0051]
α_O	0.0023	0.0004	0.0177	0.0158	$\alpha_{H\Theta}$	-0.045	-0.2298	-0.4127	-0.2216
	(0.0518)	[-0.1005;0.1093]	(0.0843)	[-0.1541;0.1892]		(23.2637)	[-2.0484;1.7861]	(14.1801)	[-1.8167;1.51]
α_{HH}	0.0203	0.0157*	0.0297	0.0242*	$\alpha_{V\Theta}$	-0.087	-0.0121	0.0035	0.0131
	(0.0175)	[0.0006;0.065]	(0.0239)	[0.0011;0.0886]		(6.913)	[-0.6986;0.7438]	(8.8375)	[-0.5508;0.636]
α_{HV}	-0.0121	-0.0077	-0.0136	-0.0086	$\alpha_{O\Theta}$	-0.0745	-0.0231	-0.171	-0.0555
	(0.0171)	[-0.0542;0.0113]	(0.0201)	[-0.0636;0.0153]		(1.7574)	[-0.4422;0.301]	(6.4923)	[-0.7336;0.604]
α_{HO}	0	0	0.0029	0.0019	$\beta_{K\Theta}$	-0.2384	0.0924	0.1017	0.0368
	(0.0037)	[-0.0078;0.0081]	(0.0063)	[-0.0078;0.0182]		(28.7591)	[-1.7005;1.9079]	(12.3429)	[-1.4335;1.2705]
α_{VV}	0.0475	0.0409*	0.0484	0.0398*	$\beta_{L\Theta}$	-0.2428	-0.0089	0.1134	0.0163
	(0.0356)	[0.0018;0.1326]	(0.0377)	[0.002;0.1402]		(19.433)	[-1.3873;1.0567]	(4.7234)	[-0.8319;0.8675]
α_{VO}	-0.0002	-0.00001	-0.0019	-0.0012	$\beta_{A\Theta}$	0.105	0.1625	0.3577	0.1354
	(0.0055)	[-0.0122;0.0112]	(0.0072)	[-0.0179;0.0117]		(14.2805)	[-1.82;2.0784]	(11.888)	[-1.2993;1.6121]
α_{OO}	0.0036	0.0027*	0.0067	0.0052*	$\sigma_{\ln D}$	0.0449	0.0439*	0.0577	0.0565*
	(0.0033)	[0.0001;0.0121]	(0.0056)	[0.0002;0.0207]		(0.0075)	[0.0331;0.0627]	(0.0093)	[0.043;0.0786]
β_K	0.8955	0.8891*	1.0845	1.081*	*Mean*	-0.0116	-0.0076(*0%)	0.0055	0.0095(*0%)
	(0.42)	[0.0924;1.725]	(0.4645)	[0.1459;1.9917]	$\lambda_{63:04}$	(0.075)	[-0.1724;0.1244]	(0.0901)	[-0.1874;0.1714]
β_L	-0.1089	-0.1037	0.0346	0.0347	*Corr.*	-0.2485	-0.2615	-0.6358	-0.6728*
	(0.308)	[-0.7193;0.4806]	(0.3242)	[-0.5942;0.6918]	$\vartheta_{st}, \vartheta_{st}^{K}$	(0.2532)	[-0.7037;0.2706]	(0.178)	[-0.8754;-0.1928]
β_A	-3.0264	-3.0552*	-3.1313	-3.1531*	*Corr.*	-0.546	-0.5636*	-0.74	-0.7571*
	(1.1813)	[-5.2678;-0.6393]	(1.1983)	[-5.4895;-0.7913]	$\vartheta_{st}, \vartheta_{st}^{L}$	(0.1478)	[-0.7806;-0.2118]	(0.0887)	[-0.8604;-0.5219]
β_{KK}	-0.053	-0.0413*	-0.0554	-0.0433*	*Corr.*	-0.7332	-0.7531*	-0.8635	-0.8747*
	(0.0453)	[-0.1679;-0.0017]	(0.0473)	[-0.1726;-0.002]	$\vartheta_{st}, \vartheta_{st}^{A}$	(0.1167)	[-0.8999;-0.4555]	(0.0565)	[-0.9385;-0.7225]
β_{LL}	-0.0414	-0.0391*	-0.0376	-0.0352*	Log	1258.77	1258.8*	1249.91	1250.38*
	(0.0243)	[-0.0948;-0.0028]	(0.0242)	[-0.0912;-0.0019]	Likel.	(19.58)	[1220.39;1297]	(15.95)	[1217.28;1279.77]
β_{AA}	0.2818	0.2819*	0.2981	0.2985*					
	(0.088)	[0.1078;0.4539]	(0.0893)	[0.1283;0.4748]					
β_{KL}	-0.0082	-0.0081	-0.0086	-0.0079	Recov.				
	(0.0204)	[-0.0473;0.0355]	(0.0201)	[-0.0487;0.0332]	Param.				
β_{KA}	0.0135	0.0136	0.0306	0.0295	β_M	0.2133	0.2124	-0.119	-0.1176
	(0.036)	[-0.0557;0.0843]	(0.0389)	[-0.0439;0.1097]		(0.3731)	[-0.5253;0.926]	(0.4047)	[-0.9363;0.6881]
β_{LA}	0.0673	0.0664*	0.0639	0.0633*	$\beta_{M\Theta}$	0.4812	-0.0851	-0.215	-0.0568
	(0.0298)	[0.011;0.1268]	(0.0285)	[0.0096;0.121]		(47.8177)	[-1.9174;1.8518]	(15.6032)	[-1.1791;1.107]
δ_{HL}	-0.0306	-0.0307	-0.0469	-0.0468	β_{MM}	-0.1108	-0.1027*	-0.1103	-0.0999*
	(0.025)	[-0.0815;0.0184]	(0.0259)	[-0.0984;0.0038]		(0.0643)	[-0.2539;-0.0131]	(0.0682)	[-0.2629;-0.0114]
δ_{VL}	-0.0162	-0.0153	-0.0047	-0.0038	β_{LM}	0.0496	0.0486	0.0463	0.0436
	(0.0295)	[-0.0758;0.0401]	(0.0278)	[-0.0613;0.0472]		(0.0318)	[-0.0039;0.117]	(0.0329)	[-0.0054;0.1189]
δ_{OL}	-0.0035	-0.0027	-0.0064	-0.0055	β_{MA}	-0.0808	-0.0804*	-0.0945	-0.0937*
	(0.0072)	[-0.0193;0.0088]	(0.0106)	[-0.0296;0.0117]		(0.0329)	[-0.1463;-0.018]	(0.035)	[-0.1653;-0.0284]
δ_{HK}	-0.0817	-0.0814*	-0.0952	-0.0954*	β_{KM}	0.0612	0.0515	0.064	0.0527
	(0.0388)	[-0.1572;-0.0046]	(0.0404)	[-0.1743;-0.0154]		(0.0507)	[-0.0044;0.185]	(0.053)	[-0.0036;0.1888]
δ_{VK}	0.0435	0.0438	0.0286	0.0295	δ_{HM}	0.1124	0.1122*	0.142	0.1424*
	(0.0352)	[-0.028;0.1121]	(0.0367)	[-0.0474;0.0963]		(0.0326)	[0.0487;0.1749]	(0.0359)	[0.0689;0.21]
δ_{OK}	0.0119	0.0106	0.0198	0.0184	δ_{VM}	-0.0272	-0.0267	-0.0239	-0.0241
	(0.0132)	[-0.011;0.042]	(0.0181)	[-0.0117;0.0592]		(0.0376)	[-0.1011;0.0448]	(0.0385)	[-0.0987;0.0537]
δ_{HA}	0.0201	0.0204	0.0249	0.0256	δ_{OM}	-0.0084	-0.0075	-0.0134	-0.0124
	(0.0143)	[-0.009;0.0479]	(0.0194)	[-0.014;0.0615]		(0.0109)	[-0.0327;0.0107]	(0.0156)	[-0.047;0.015]

Table 5. 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]
Pacific Region				
CA	0.62	0.81	1.22	0.82
	(2.5)	[-10.68; 5.41]	(2.41)	[-2.67; 8.09]
OR	0.58	-0.05	1.53	1.62
	(1.7)	[-3.69; 4.28]	(2.62)	[-3.91; 7.28]
WA	1.21	0.63	1.79	1.66
	(2.68)	[-4.58; 6.34]	(4.03)	[-9.19; 8.89]
Central Region				
IA	0.84	0.5	0.59	0.99
	(6.76)	[-19.09; 20.66]	(4.19)	[-11.21; 9.23]
IL	0.24	-0.46	0.02	0.1
	(3.78)	[-9.17; 7.13]	(1.95)	[-5.02; 5.48]
IN	1.03	1.44	0.52	0.57
	(6.01)	[-10.5; 22.89]	(3.33)	[-6.95; 8.5]
MI	1.22	1.32	0.59	0.61
	(9.39)	[-17.1; 53.9]	(3.1)	[-6.6; 10.53]
MN	1.64	0.61	0.96	0.71
	(9.83)	[-22.5; 42.59]	(3.7)	[-8.4; 11.55]
MO	0.84	-0.15	0.41	0.82
	(5.36)	[-9.38; 19.04]	(2.8)	[-5.85; 6.65]
OH	0.47	0.25	0.34	-0.14
	(4.59)	[-12.72; 13.85]	(2.97)	[-6.12; 7.1]
WI	1.93	0.48	0.55	0.41
	(13.88)	[-21.52; 74.52]	(4.16)	[-6.91; 10.31]
Southern Plains				
AR	1.95	0.65	1.23	1.18
	(16.66)	[-27.23; 40.57]	(7.95)	[-15.28; 19.58]
LA	1.21	3.01	0.95	2.75
	(9.83)	[-16.99; 19.9]	(7.26)	[-14.39; 12.5]
MS	-1.45	3.2	0.16	1.06
	(16.93)	[-53.17; 25.16]	(9.37)	[-23.50; 20.24]
OK	1.29	1.9	1.24	2.44
	(17.22)	[-55.84; 41.05]	(8.84)	[-21.51; 16.37]
TX	3.12	1.56	0.40	0.01
	(18.81)	[-33.96; 73.67]	(7.98)	[-16.82; 14.27]

Table 6. 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]
Pacific Region				
CA	0.73	1.31	0.10	0.18
	(5.42)	[-13.45; 16.66]	(1.39)	[-4.04; 3.67]
OR	0.83	1.03	-0.40	0.01
	(3.43)	[-11.62; 8.14]	(2.73)	[-7.09; 5.53]
WA	0.32	0.72	-0.33	0.12
	(4.11)	[-10.39; 8.25]	(4.08)	[-11.59; 8.53]
Central Region				
IA	-0.54	-0.15	-0.18	-0.05
	(2.59)	[-8.28; 4.18]	(1.96)	[-6.75; 5.54]
IL	0.45	0.73	0.66	1.08
	(7.15)	[-21.04; 16.74]	(4.40)	[-12.65; 14.81]
IN	-0.35	0.42	0.15	0.40
	(4.63)	[-14.90; 8.67]	(1.99)	[-4.17; 7.28]
MI	-0.30	0.35	-0.02	0.25
	(10.58)	[-61.89; 18.48]	(2.61)	[-14.34; 5.52]
MN	-1.19	0.01	-0.35	0.30
	(9.38)	[-49.52; 22.11]	(2.82)	[-7.61; 3.83]
MO	-0.54	-0.17	-0.16	-0.25
	(3.17)	[-11.97; 6.96]	(1.42)	[-3.54; 3.04]
OH	0.08	1.10	0.09	0.10
	(3.71)	[-10.20; 5.79]	(2.28)	[-4.67; 4.2]
WI	-1.72	-0.23	-0.37	0.32
	(14.7)	[-84.09; 25.92]	(3.58)	[-14.53; 6.42]
Southern Plains				
AR	-0.15	1.74	0.56	1.20
	(13.99)	[-38.36; 25.72]	(7.36)	[-14.57; 15.36]
LA	-0.46	-1.52	-0.62	-0.62
	(5.04)	[-10.81; 10.47]	(4.69)	[-9.44; 9.83]
MS	2.1	0.75	0.88	0.04
	(13.59)	[-23.49; 48.36]	(8.34)	[-19.02; 24.70]
OK	-0.43	-0.04	-1.12	-3.37
	(15.64)	[-37.59; 54.14]	(9.92)	[-15.76; 25.82]
TX	-2.02	0.64	0.37	-0.11
	(18.69)	[-84.89; 31.46]	(8.60)	[-26.68; 20.29]

Table 7. 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]
Pacific Region				
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]
Central Region				
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 (1.27)	0.08 [-2.6; 2.68]	0.36 (1.12)	0.08 [-1.84; 2.84]
Southern Plains				
AR	-0.76 (1.81)	-0.59 [-4.23; 2.83]	-1.38 (2.61)	-1.36 [-7.31; 3.92]
LA	-0.61 (1.60)	-0.57 [-3.30; 2.79]	-1.18 (2.28)	-1.30 [-6.01; 3.77]
MS	-0.63 (1.65)	-0.57 [-3.87; 2.54]	-1.29 (2.43)	-1.48 [-7.5; 3.55]
OK	-0.38 (0.91)	-0.27 [-2.14; 1.42]	-0.94 (1.77)	-0.77 [-5.23; 2.99]
TX	-0.45 (1.12)	-0.36 [-2.51; 1.80]	-1.14 (2.08)	-1.25 [-5.78; 3.56]

Table 8. 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]
Pacific Region				
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]
Central Region				
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
	(0.33)	[0.41; 1.48]	(0.21)	[0.38; 1.08]
Southern Plains				
AR	0.58	0.57	1.33	1.26
	(2.18)	[-3.24; 4.25]	(2.81)	[-3.56; 6.12]
LA	1.18	1.07	1.95	1.76
	(2.10)	[-2.5; 4.68]	(2.71)	[-2.76; 6.48]
MS	1.54	1.43	2.38	2.17
	(1.57)	[-1.16; 4.20]	(2.19)	[-1.38; 6.15]
OK	0.85	0.73	1.56	1.37
	(1.00)	[-0.89; 2.58]	(1.64)	[-1.26; 4.42]
TX	1.12	1.01	1.79	1.61
	(1.15)	[-0.89; 3.12]	(1.93)	[-1.60; 5.15]

Table 9. 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]
Pacific Region				
CA	-1.28	-0.87	-0.71	-0.52
	(4.40)	[-15.54; 7.15]	(3.56)	[-9.05; 6.92]
OR	-0.37	0.08	0.33	0.35
	(5.94)	[-15.02; 25.54]	(3.73)	[-6.4; 8.45]
WA	-1.00	-1.24	-0.56	-1.02
	(3.98)	[-13.43; 7.84]	(3.37)	[-8.33; 5.43]
Central Region				
IA	-0.30	0.08	-0.33	-0.03
	(4.01)	[-13.18; 11.01]	(4.02)	[-15.44; 9.06]
IL	-0.10	-0.15	-0.05	-0.21
	(2.78)	[-5.93; 6.40]	(2.59)	[-5.79; 6.17]
IN	-0.34	0.08	-0.38	-0.36
	(3.04)	[-6.28; 5.98]	(3.25)	[-8.22; 5.35]
MI	-0.23	0.10	-0.18	0.01
	(4.36)	[-9.06; 8.8]	(4.47)	[-9.26; 9]
MN	-0.42	-0.21	-0.28	0.33
	(3.93)	[-10.87; 8.11]	(3.62)	[-8.96; 8.76]
MO	-0.20	0.07	-0.11	-0.42
	(5.02)	[-13.25; 11.05]	(4.47)	[-10.59; 10.11]
OH	-0.27	-0.83	-0.32	0.03
	(4.32)	[-11.27; 8.61]	(4.73)	[-11.69; 8.37]
WI	-0.77	-0.77	-0.68	-0.54
	(5.3)	(5.3)	(5.26)	[-19.6; 7.41]
Southern Plains				
AR	-0.03	-0.04	0.22	-0.06
	(6.19)	[-11.81; 16.95]	(6.84)	[-11.05; 17.76]
LA	0.18	0.34	0.25	0.63
	(5.01)	[-13.39; 9.19]	(5.99)	[-15.05; 11.1]
MS	-0.02	-0.01	0.05	0.72
	(5.72)	[-18; 14.69]	(7.24)	[-21.29; 15.2]
OK	-0.19	-0.68	-0.02	0.27
	(6.58)	[-11.81; 15.25]	(7.92)	[-14.14; 15.19]
TX	-0.32	-0.84	-0.07	0.21
	(6.27)	[-15.97; 14.28]	(6.99)	[-19.31; 15.39]

Table 10. 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]
Pacific Region				
CA	-0.17	-0.13	0.06	0.05
	(0.18)	[-0.6; 0.11]	(0.08)	[-0.11; 0.24]
OR	-0.25	-0.05	-0.02	0.00
	(0.43)	[-1.25; 0.44]	(0.1)	[-0.35; 0.13]
WA	-0.16	-0.04	0.03	0.03
	(0.27)	[-0.87; 0.13]	(0.09)	[-0.14; 0.24]
Central Region				
IA	-0.01	-0.02	0.00	0.00
	(0.06)	[-0.14; 0.12]	(0.04)	[-0.08; 0.12]
IL	-0.07	-0.02	-0.04	-0.01
	(0.16)	[-0.48; 0.29]	(0.09)	[-0.26; 0.1]
IN	-0.07	-0.04	-0.05	-0.03
	(0.13)	[-0.47; 0.19]	(0.09)	[-0.33; 0.13]
MI	-0.19	-0.03	-0.15	-0.08
	(0.37)	[-1; 0.3]	(0.28)	[-0.77; 0.25]
MN	-0.11	-0.09	-0.05	-0.01
	(0.3)	[-0.78; 0.54]	(0.17)	[-0.46; 0.28]
MO	-0.07	-0.02	-0.03	0.00
	(0.33)	[-1.07; 0.34]	(0.18)	[-0.63; 0.25]
OH	-0.13	-0.03	-0.08	-0.04
	(0.26)	[-0.94; 0.31]	(0.16)	[-0.52; 0.15]
WI	-0.16	-0.08	-0.08	-0.05
	(0.26)	[-0.76; 0.23]	(0.14)	[-0.41; 0.17]
Southern Plains				
AR	-0.11	-0.12	-0.13	-0.16
	(0.45)	[-1.26; 0.85]	(0.57)	[-1.37; 1.11]
LA	-0.18	-0.21	-0.31	-0.43
	(0.33)	[-0.96; 0.63]	(0.50)	[-1.44; 0.82]
MS	-0.52	-0.68	-0.72	-0.97
	(0.6)	[-1.48; 0.89]	(0.89)	[-1.94; 1.61]
OK	-0.11	-0.04	-0.15	-0.04
	(0.65)	[-1.58; 0.95]	(0.84)	[-2.00; 1.27]
TX	-0.29	-0.06	-0.38	-0.13
	(0.81)	[-2.31; 1.08]	(1.01)	[-2.80; 1.28]

Table 11. 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]
Pacific Region				
CA	0.19	0.41	0.14	0.11
	(2.3)	[-5.72; 6.92]	(1.29)	[-2.29; 3.29]
OR	0.26	-0.03	0.24	-0.06
	(2.12)	[-3.33; 4.27]	(1.92)	[-3.69; 4.77]
WA	0.24	0.33	0.17	0.24
	(1.95)	[-4.3; 5.78]	(2.00)	[-5.87; 5.14]
Central Region				
IA	0.15	0.35	0.19	0.16
	(2.01)	[-5.81; 6.09]	(2.06)	[-5.1; 7.18]
IL	0.08	0.27	0.03	0.32
	(1.49)	[-4.85; 3.34]	(1.39)	[-4.24; 2.85]
IN	0.07	0.09	0.05	0.05
	(1.84)	[-3.25; 5.00]	(1.91)	[-3.69; 6.44]
MI	-0.16	0.09	-0.27	0.03
	(3.81)	[-10.33; 8.96]	(3.37)	[-7.67; 6.65]
MN	0.41	0.28	0.37	0.30
	(3.17)	[-10.52; 7.06]	(2.79)	[-8.78; 6.48]
MO	-0.13	-0.06	-0.13	0.20
	(3.36)	[-11.42; 10.95]	(2.90)	[-8.39; 9.01]
OH	0.20	0.15	0.13	0.30
	(2.42)	[-6.09; 5.80]	(2.58)	[-6.46; 5.04]
WI	0.63	0.22	0.60	0.06
	(3.25)	[-4.36; 15.90]	(2.94)	[-4.99; 13.54]
Southern Plains				
AR	-0.13	-0.05	-0.22	-0.27
	(3.18)	[-9.87; 6.12]	(3.56)	[-8.42; 6.58]
LA	0.10	-0.27	0.02	-0.10
	(5.20)	[-16.52; 13.74]	(5.58)	[-16.72; 13.54]
MS	-0.18	0.31	-0.28	0.09
	(4.46)	[-8.99; 12.05]	(5.22)	[-8.82; 15.30]
OK	-0.46	-0.06	-0.55	-0.12
	(4.03)	[-10.18; 10.74]	(4.28)	[-9.86; 12.62]
TX	-0.24	-0.63	-0.32	-0.88
	(3.27)	[-9.08; 7.08]	(3.75)	[-9.97; 8.15]

Table 12. 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	-0.02	-0.10	0.32
	(0.10)	[-0.47; 0.08]	(1.88)	[-4.68; 2.98]
OR	-0.12	-0.03	0.02	0.20
	(0.27)	[-1.52; 0.07]	(3.61)	[-8.16; 7.52]
WA	-0.11	-0.03	-0.03	-0.37
	(0.18)	[-0.69; 0.06]	(4.04)	[-11.77; 7.91]
IA	-0.10	-0.05	0.00	-0.15
	(0.24)	[-0.71; 0.57]	(1.43)	[-2.68; 3.92]
IL	-0.03	-0.03	0.08	0.27
	(0.27)	[-0.89; 0.83]	(2.44)	[-4.84; 4.85]
IN	-0.01	-0.01	0.01	0.37
	(0.30)	[-1.15; 1.19]	(1.93)	[-4.91; 4.17]
MI	-0.07	-0.03	0.01	-0.07
	(0.14)	[-0.58; 0.11]	(1.11)	[-3.00; 1.82]
MN	-0.08	-0.02	-0.07	0.01
	(0.48)	[-2.53; 0.56]	(1.36)	[-3.24; 2.94]
MO	-0.03	-0.01	0.07	0.44
	(0.27)	[-1.16; 0.81]	(3.46)	[-11.00; 8.59]
OH	-0.05	-0.03	0.02	0.04
	(0.24)	[-1.41; 0.37]	(1.77)	[-3.74; 4.02]
WI	-0.07	-0.05	-0.01	-0.19
	(0.27)	[-0.87; 0.73]	(1.31)	[-2.80; 2.47]
Southern Plains				
AR	-0.16	-0.08	-0.24	-0.37
	(0.34)	[-1.49; 0.27]	(2.64)	[-4.46; 6.58]
LA	-0.07	-0.01	-0.18	-0.52
	(0.18)	[-0.79; 0.11]	(2.23)	[-5.56; 4.11]
MS	-0.14	-0.02	-0.24	0.35
	(0.49)	[-2.90; 0.33]	(2.53)	[-4.39; 4.67]
OK	-0.09	-0.04	-0.05	0.19
	(0.21)	[-1.05; 0.27]	(3.23)	[-6.88; 5.93]
TX	-0.08	-0.02	-0.10	-0.09
	(0.20)	[-0.86; 0.12]	(2.39)	[-7.45; 5.27]

Table 13. Descriptive Statistics of the negative of the Annual Median Estimates of the Input Price Aggregate Effect, $-\widehat{IPAE}$ (in Percent)

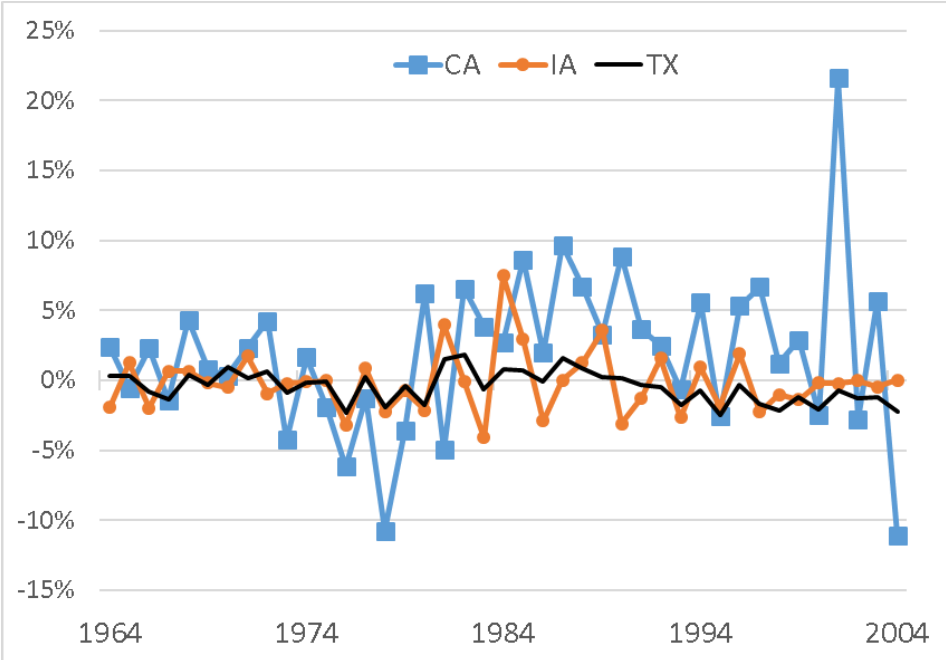
State	Model 1: Original Variables		Model 2: Weather-Filtered Variables	
	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]	Mean Annual Median (StDev of Annual Medians)	Median of Annual Medians [Range of Annual Medians]
Pacific Region				
CA	0.22	0.07	0.30	0.49
	(0.44)	[-0.19; 2.53]	(1.8)	[-4.24; 3.92]
OR	0.26	0.13	0.25	0.25
	(0.48)	[-0.05; 2.83]	(1.46)	[-4.04; 3.21]
WA	-0.13	0.14	-0.15	-0.02
	(1.32)	[-5.04; 3.03]	(1.74)	[-4.44; 3.71]
Central Region				
IA	0.41	0.23	0.44	0.52
	(0.55)	[-0.02; 3.07]	(3.22)	[-6.72; 6.18]
IL	0.40	0.23	0.38	-0.22
	(0.72)	[-0.01; 4.23]	(3.33)	[-5.25; 7.78]
IN	0.41	0.25	0.33	0.39
	(0.62)	[-0.04; 3.7]	(2.78)	[-5.18; 6.96]
MI	0.58	0.33	0.50	0.18
	(0.98)	[-0.09; 5.89]	(2.98)	[-7.88; 7.65]
MN	0.38	0.15	0.47	0.6
	(0.55)	[-0.04; 2.72]	(3.8)	[-6.78; 8.99]
MO	0.49	0.22	0.51	0.69
	(0.72)	[-0.04; 3.55]	(4.08)	[-10.21; 12.91]
OH	0.36	0.20	0.31	0.79
	(0.55)	[-0.12; 2.89]	(2.84)	[-5.97; 5.28]
WI	0.36	0.19	0.31	0.71
	(0.70)	[-0.09; 4.29]	(3.24)	[-6.78; 7.15]
Southern Plains				
AR	0.31	0.16	0.29	-0.03
	(0.46)	[-0.06; 2.49]	(1.33)	[-1.94; 2.92]
LA	0.47	0.14	0.44	0.22
	(0.75)	[-0.17; 3.7]	(1.81)	[-2.54; 7.05]
MS	0.39	0.23	0.38	0.26
	(0.49)	[-0.03; 2.63]	(1.58)	[-2.55; 4.22]
OK	0.47	0.28	0.39	0.35
	(0.54)	[-0.03; 2.53]	(1.93)	[-6.04; 5.00]
TX	0.37	0.12	0.36	0.24
	(0.6)	[-0.09; 3.56]	(1.68)	[-2.84; 4.96]

Table 14. Descriptive Statistics of the Annual Median Estimates of Total Factor Productivity Change, $\widehat{T\dot{F}P}$ (in Percent)

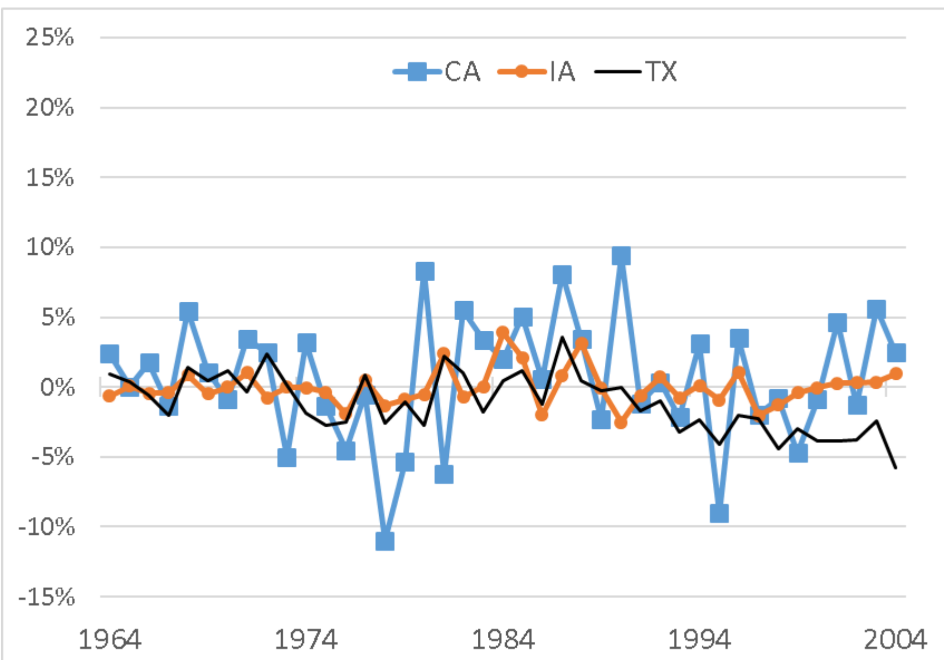
State	$T\dot{F}P$ USDA		$\widehat{T\dot{F}P}$ Model 1: Original Variables		$\widehat{T\dot{F}P}^{WF}$ Model 2: Weather-Filtered Variables		$\widehat{T\dot{F}P} = \widehat{T\dot{F}P}^{WF} + \widehat{NWEFF}$ Model 2: Weather-Filtered Variables	
	Mean (StDev)	Correlation with USDA estimates [Range]	Mean 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]
Pacific Region								
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]
Central Region								
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]

Table 14. Descriptive Statistics of the Annual Median Estimates of Total Factor Productivity Change, $\widehat{T\dot{F}P}$ (in Percent) (Continued)

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		$\widehat{T\dot{F}P} = \widehat{T\dot{F}P}^{WF} + N\widehat{WEFF}$ 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]
Central Region								
WI	1.56	1.00	1.32	0.995	1.42	0.703	1.39	0.997
	(5.49)	[-8.33; 14.84]	(5.47)	[-8.81; 14.29]	(6.36)	[-12.17; 17.47]	(5.56)	[-8.67; 15.14]
Southern Plains								
AR	1.84	1.00	1.50	0.993	1.65	0.836	1.80	0.997
	(9.7)	[-20.23; 25.27]	(9.62)	[-21.96; 24.91]	(8.82)	[-15.45; 26.79]	(9.72)	[-20.25; 25.08]
LA	1.72	1.00	1.82	0.996	1.32	0.889	1.59	0.996
	(9.34)	[-16.91; 19.18]	(9.81)	[-17.58; 20.29]	(8.03)	[-12.32; 18.58]	(9.69)	[-17.29; 20.27]
MS	1.64	1.00	1.09	0.992	1.33	0.879	1.52	0.994
	(8.78)	[-20.58; 22.37]	(9.11)	[-21.36; 21.49]	(8.12)	[-13.54; 16.25]	(9.08)	[-21.14; 22.31]
OK	0.93	1.00	0.94	0.992	0.37	0.693	0.51	0.985
	(7.54)	[-16.67; 21.56]	(7.91)	[-18.12; 21.36]	(7.91)	[-21.54; 19.37]	(7.58)	[-16.76; 17.97]
TX	1.20	1.00	1.20	0.990	0.90	0.767	0.96	0.981
	(6.42)	[-12.38; 14.59]	(6.49)	[-12.77; 14.90]	(6.08)	[-13.16; 16.05]	(6.65)	[-13.17; 14.85]

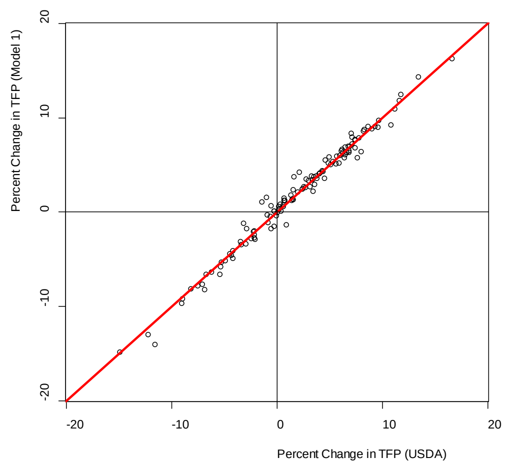


Panel a. Adjusted technical change estimates from Model 1

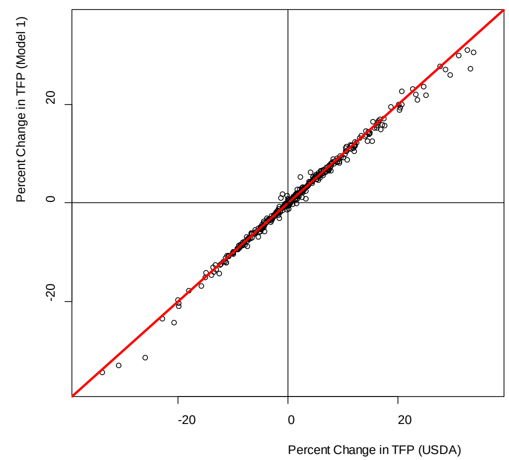


Panel a. Adjusted technical change estimates from Model 2

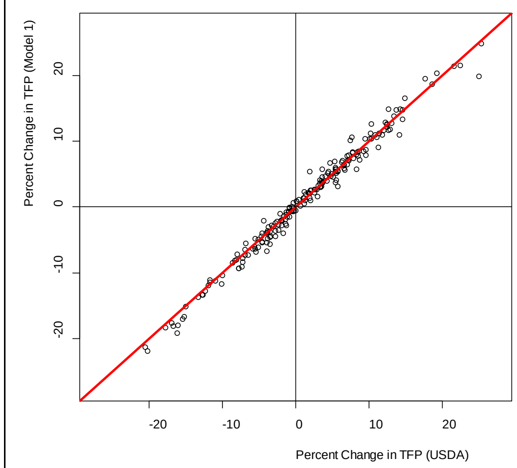
Figure 1. Annual median technical change estimates, $\frac{C_v(w_v,X_v)}{C_o(w,X)}\widehat{TC}$, for California, Iowa, and Texas, 1964-2004



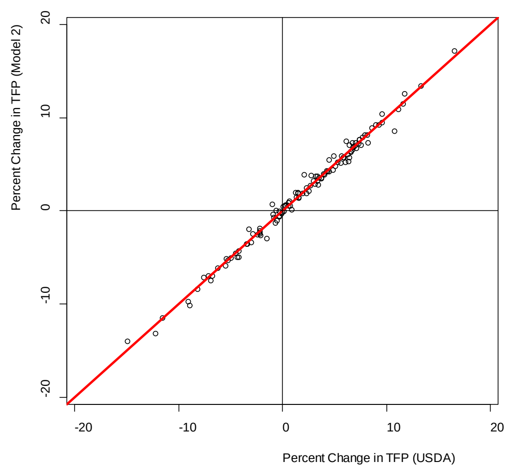
Panel a. $T\dot{F}P$ in Pacific Region: USDA & Model 1



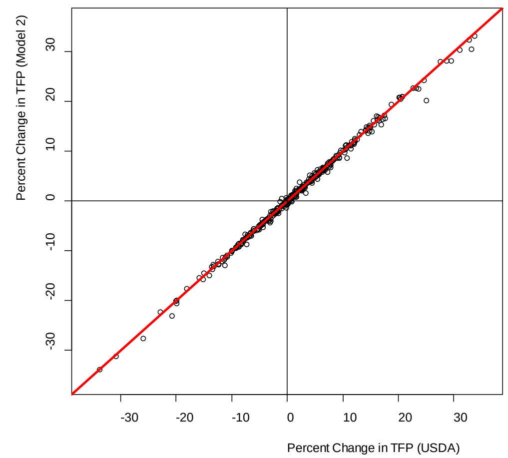
Panel b. $T\dot{F}P$ in Central Region: USDA & Model 1



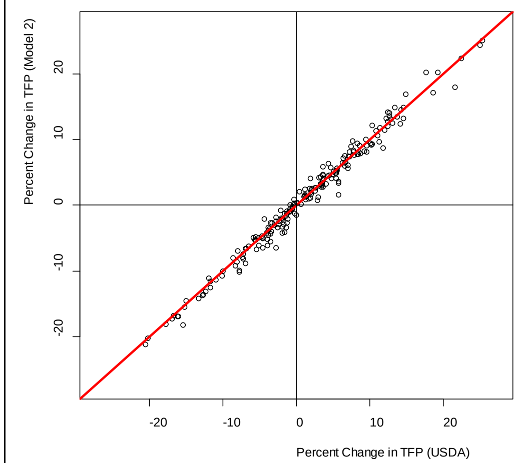
Panel c. $T\dot{F}P$ in Southern Plains: USDA & Model 1



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

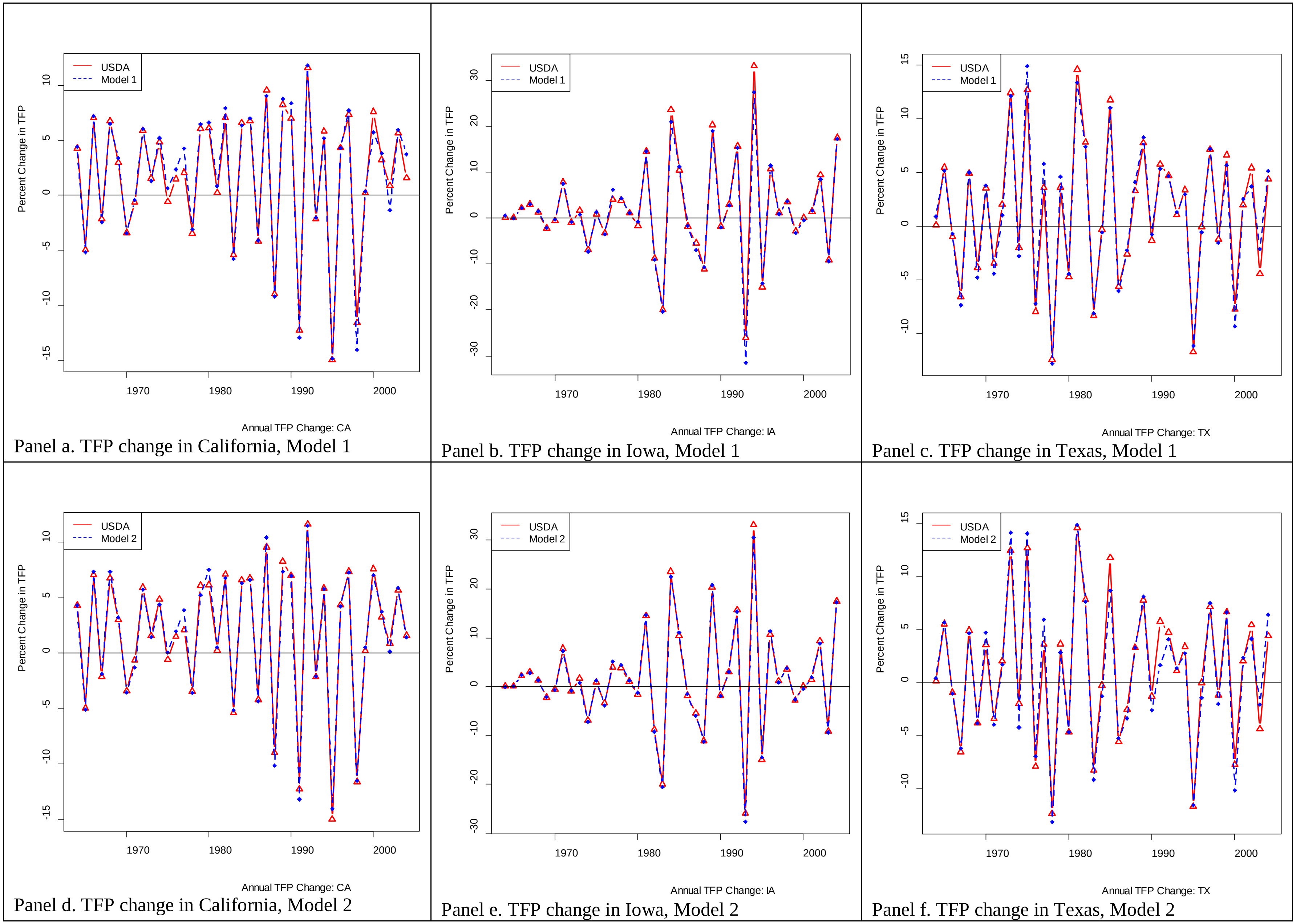


Panel e. $T\dot{F}P$ in Central Region: USDA & Model 2



Panel f. $T\dot{F}P$ in Southern Plains: USDA & Model 2

Figure 2. $T\dot{F}P$ estimates: USDA vs. ours



Panel a. TFP change in California, Model 1

Panel b. TFP change in Iowa, Model 1

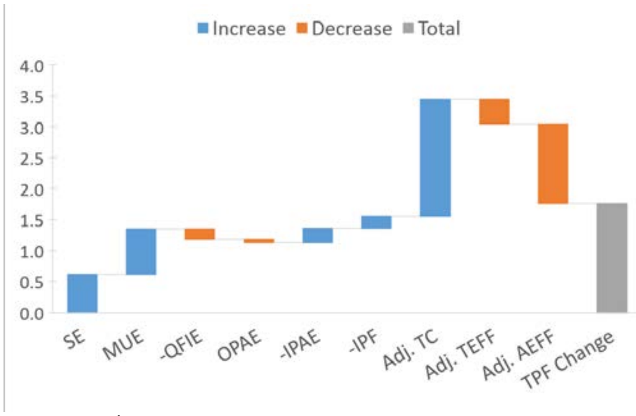
Panel c. TFP change in Texas, Model 1

Panel d. TFP change in California, Model 2

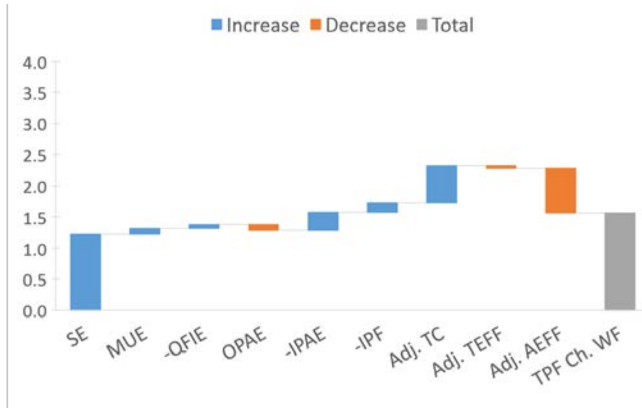
Panel e. TFP change in Iowa, Model 2

Panel f. TFP change in Texas, Model 2

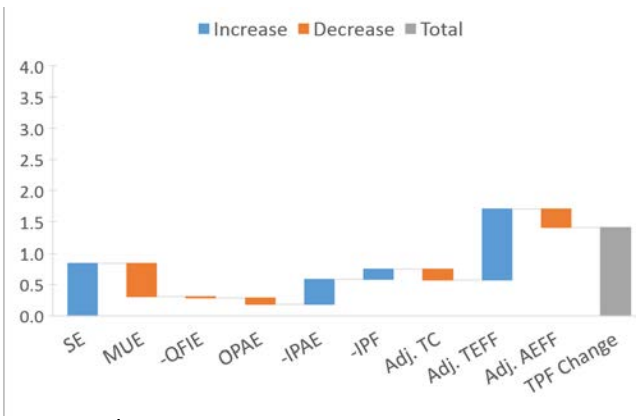
Figure 3. Annual $\dot{TFP}$ for selected states



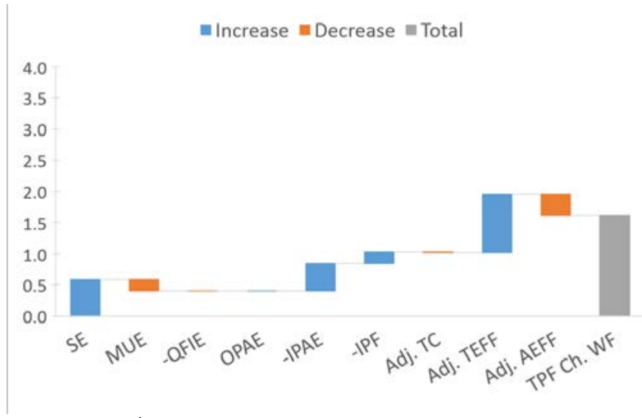
Panel a. $T\dot{F}P$ in California, Model 1



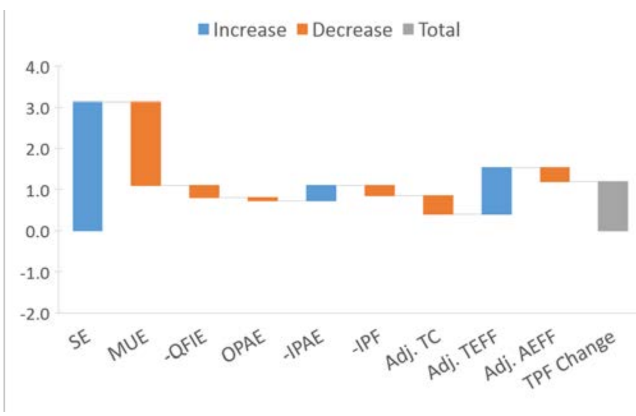
Panel b. $TF\dot{P}^{WF}$ in California, Model 2



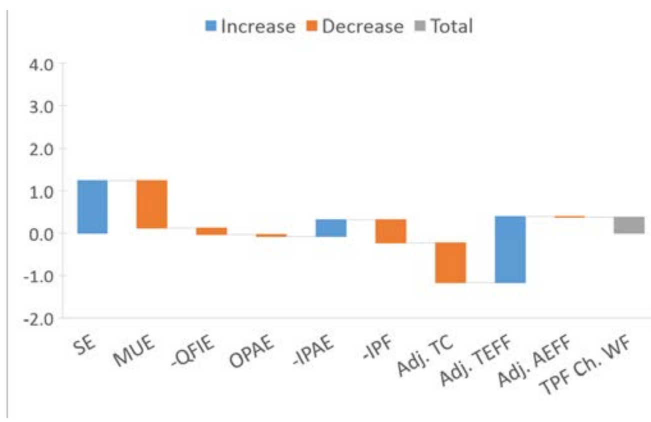
Panel c. $T\dot{F}P$ in Iowa, Model 1



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



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



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

Figure 4. Average contribution of each component to $T\dot{F}P$ and $TF\dot{P}^{WF}$ for selected states, by Model

[1] The list of variables included public research, public research spill-in, extension, education, health care access, farm size, family-to-total labor ratio, terms of trade, precipitation, growing degree days, damaging degree days, agro-temperature, agro-precipitation, and regional and payment-in-kind dummies (Sabasi and Shumway 2018).

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

[3] When the scale of operation is optimal this term becomes null, because $RTS = 1$.

[4] Note that a minimum-cost combination of inputs is a theoretical construct based on the observed prices, quasi-fixed input levels, and output levels 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, as well as input and output costs of adjustment.

[5] Duality between the cost function and the input distance function, such that $C(\underline{Y}, w_v, X_q; t) \equiv \min_{X_{v_i}}\{\sum_i w_{v_i} X_{v_i}: D(\underline{Y}, X_v, X_q; t) \geq 1;\ w_{v_i} > 0; i = 1, \ldots, I-1\}$, 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).

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

[7] An alternative approach to incorporating weather effects into our model is to develop indexes of weather conditions and to treat them as exogenous and free inputs 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 the "optimal" season for a particular region (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).

[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 article is aggregated at the state-level, we are not able to use the current ERS regions.

[9] Yan and Shumway (2016), based on a long-term study (1910-2011) of U.S. agriculture netputs, conclude that crop and livestock outputs, and labor, fertilizer and capital inputs exhibited quasi-fixity in response to market change and stochastic climate change. However, while the adjustment period for both outputs, labor and fertilizer to their long-run equilibrium averaged 5 years or less, the adjustment period for capital averaged 20 years. Furthermore, that study reports that capital fixity could not be rejected at the 5% level of significance.

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

[11] 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. By having priors with standard deviations at least 15 times larger than the corresponding posteriors, our approach ensures that posteriors are driven mostly by the data rather than the priors.

[12] In this instance, only a single correlation coefficient is estimated because the covariance matrix is of size (2 × 2). Therefore, a Uniform(-1, 1) prior is used for the correlation coefficient instead of a Cholesky LKJ Correlation Distribution.

[13] The coefficients corresponding to the logarithms of the original variables were computed ex post by applying the appropriate reverse transformations to the estimated coefficients for the standardized variables.

[14] That is, we use the fact that a model $y = x\, b_x + z\, b_z + error$ with regressors x and z and coefficients b_x and b_z can be reparameterized as $y = w\, b_w + z\, b_z + error$, where $w \equiv x\, \Gamma$ are the principal components of x, $b_w \equiv \Gamma^{-1}\, b_x$, and Γ is a square matrix of principal component weights. Therefore, coefficients b_x in the former model can be computed by estimating the reparameterized model, by calculating $b_x \equiv \Gamma\, b_w$. The Stan Development Team (2019) recommends reparameterization using the QR decomposition, but principal components performed better in the present problem.

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

[16] California, Iowa, Illinois, Indiana, Michigan, Missouri, Ohio, Arkansas, Louisiana, Mississippi, Oklahoma, and Texas.

[17] Oregon, Washington, Minnesota, and Wisconsin.

[18] 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 $TF\dot{P}^{WF}$ through time without making a strong assumption about the relative value of both indexes (in levels) at one point in time. Mathematically, the problem resides in the unknown value of the arbitrary constant of integration for $\int_{t_0}^{T} TF\dot{P}^{WF}\, dt$.