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# The role of energy productivity in U.S. agriculture

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ABSTRACT

This paper investigates the role of energy on U.S. agricultural productivity using panel data at the state level for the period 1960–2004. We first provide a historical account of energy use in U.S. agriculture. To do this we rely on the Bennet cost indicator to study how the price and volume components of energy costs have developed over time. We then proceed to analyze the contribution of energy to productivity in U.S. agriculture employing the Bennet–Bowley productivity indicator. An important feature of the Bennet–Bowley indicator is its direct association with the change in (normalized) profits. Thus our study is also able to analyze the link between profitability and productivity. Panel regression estimates indicate that energy prices have a negative effect on profitability in the U.S. agricultural sector. We also find that energy productivity has generally remained below total farm productivity following the 1973–1974 global energy crisis.



## 1. Introduction

In this study we investigate the role that energy plays in the U.S. agricultural sector, both in terms of its role as a factor of production and its role as a contributor to productivity growth. Our analysis employs a unique data series compiled by the U.S. Department of Agriculture's Economic Research Service (ERS). The data comprise a state-by-year panel, which will allow us to assess the impact of technological advances over the study period as well as the effect of volatile energy prices. Of particular interest are the effects of major energy market shocks (e.g. the oil price shocks of the 1970s) on energy productivity and the profitability of the U.S. agriculture. The data set consists of three outputs and six inputs; the latter include direct energy use in agriculture as well as indirect energy use as, for example, consumption of agricultural chemicals.[1] Both price and quantity data are available. A detailed description of the data set is given in Section 3 below.

First we give an historical accounting of energy consumption in U.S. agriculture. While direct energy consumption in the agricultural sector represents only a very small fraction of the total U.S. energy use, changes in the energy market can have a large impact on costs and, therefore, on profitability of the sector as well as on food prices.[2] The effects of energy costs on profitability may also be greatly exacerbated by changes in fertilizer and pesticide costs, both of which are significant energy users. Here we rely on a Bennet (1920) indicator decomposition of profit into price and volume indicators, which can further be decomposed into changes over time and space. These decompositions are possible due to the additive structure of the Bennet indicator. Such decompositions are not possible with the more familiar Fisher and Törnqvist indexes. Thus our work provides an additional tool for the analysis of the role of energy in agriculture.

Secondly we study the contribution of energy to productivity growth in U.S. agriculture. Again we use an additive measure, namely the

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[1] Energy inputs feature in every stage of agricultural production, from making and applying chemicals to fueling farm machinery used in tillage and harvesting of crops, and to electricity for livestock housing facilities. Such reliance on energy consumption has left farmers vulnerable to high energy costs and volatile energy market fluctuations, thereby highlighting the importance of efficient use of energy for farm profitability and for more sustainable agricultural practices (see Levine, 2012).

[2] For example, Wang and McPhail (2014) report that in addition to global food demand, energy shocks also play an important role in explaining recent rapid increases in food prices.

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Bennet (1920) productivity indicator.[3] This indicator requires data on both prices and quantities of outputs and inputs, much like the Fisher and Törnqvist indexes. And, like the Fisher and Törnqvist indexes, it can be derived based on a test approach (see Diewert, 2005) or through its dual, the Luenberger productivity indicator (see Chambers, 2002; Chambers et al., 1996). The Bennet (1920) indicator satisfies many desirable properties. In this study, one of the most important is its additive structure which allows for straightforward aggregation and disaggregation. Thus we can aggregate direct energy use to get an overall contribution of energy to productivity growth. We can also aggregate over regions or time periods, again introducing a useful analytical tool.

## 2. Indicators

The purpose of this section is to provide a short introduction to indicator theory as a means of summarizing economic variables (see Chambers, 2002 or Färe et al., 2008, for more detailed information). We follow Diewert (2005) and refer to summary measures constructed as ratios as indexes and summary measures constructed as differences as indicators. Ratio measures are relatively familiar; price and quantity indexes, as well as productivity indexes, are examples. Yet difference measures have very simple aggregation properties. The 'total' difference is the sum of the sub-aggregates, which makes them useful when summarizing panel data, as we have here.[4] Another advantage of using differences rather than ratios is that they circumvent problems arising from the presence of zeroes in the data.[5] Use of differences is also a convenient tool to analyze the sources of profit change from price and quantity changes or to determine the sources of deviations of actual values from budgeted or optimal values (see Fox, 2006).

We begin with some notation. Let $x^{\tau} \in R_{+}^{N}, \tau = t, t+1$, be a nonnegative vector $x^{\tau} = (x_1^{\tau},..., x_N^{\tau})$ of inputs at time $\tau$ and let $w^{\tau} \in R_{+}^{N}$, $w^{\tau} = (w_1^{\tau},..., w_N^{\tau})$, $\tau = t, t+1$, be its corresponding vector of input prices. Costs at $\tau$ are defined as the inner product

$$C^{\tau} = w^{\tau} x^{\tau} = \sum_{n=1}^{N} w_n^{\tau} x_n^{\tau}. \tag{1}$$

What we call the Bennet (1920) cost indicator (or cost change indicator) is defined as the cost difference

$$C^{t+1} - C^{t} \tag{2}$$

which, following Bennet (1920), can be decomposed into two indicators: a price indicator

$$W_t^{t+1} = \frac{1}{2}\left(x^{t+1} + x^{t}\right)\left(w^{t+1} - w^{t}\right) \tag{3}$$

and a volume (quantity) indicator

$$X_t^{t+1} = \frac{1}{2}\left(w^{t+1} + w^{t}\right)\left(x^{t+1} - x^{t}\right) \tag{4}$$

with the property that

$$C^{t+1} - C^{t} = W_t^{t+1} + X_t^{t+1}. \tag{5}$$

The price indicator is the additive analog of a price index. Here the simple average of the input quantities serves as the weight for the change in the input prices. Similarly, in the volume indicator, the simple average of the input prices serves as the weight for the change in input quantities. For these indicators to make sense, the prices must be 'deflated' by some general measure (see Balk, 2008, 2010; Chambers, 2001, 2002; Chambers and Färe, 1998).

The Bennet indicator in Eq. (5) has been derived by Diewert (2005) using the test approach by solving a functional equation based on tests or axioms. He shows that it is the 'best' indicator in the sense that it satisfies the 'most' axioms or tests including the time reversal test.[6] This indicator has also been derived by Chambers (2002) from the Luenberger input indicator, which provides the theoretical connection to the underlying technology. This connection required invoking the quadratic approximation lemma due to Diewert (1976) and a quadratic functional form for the directional input distance function which represents technology.[7] This yields a price normalized Bennet indicator, which is independent of the unit of measurement.

We follow Chambers (2002) to define the Bennet cost indicator in terms of input prices normalized by the value of the directional vector. In particular, we set the directional vector equal to the sample average of inputs, i.e. we set $g_x = \bar{x}$. The normalized price indicator is then given by:

$$\widetilde{W}_t^{t+1} = \frac{1}{2}\left(x^{t+1} + x^{t}\right)\left(\frac{w^{t+1}}{w^{t+1}\bar{x}} - \frac{w^{t}}{w^{t}\bar{x}}\right) \tag{3'}$$

and the normalized volume (quantity) indicator as:

$$\widetilde{X}_t^{t+1} = \frac{1}{2}\left(\frac{w^{t+1}}{w^{t+1}\bar{x}} + \frac{w^{t}}{w^{t}\bar{x}}\right)\left(x^{t+1} - x^{t}\right) \tag{4'}$$

with the property that

$$\widetilde{C}^{t+1} - \widetilde{C}^{t} = \widetilde{W}_t^{t+1} + \widetilde{X}_t^{t+1} \tag{5'}$$

where $\bar{x}$ is the sample average input bundle. This normalization comes naturally from the dual relationship between the price-based Bennet indicator with the Luenberger input indicator which uses directional distance functions rather than prices to aggregate inputs.[8]

In this paper we use an expression like that in Eq. (5′) to study how the price and volume components of energy cost have developed over the 1960–2004 period. Since costs are additive, total and partial cost indicators can be readily constructed.

[3] This indicator is as also known as the Bennet–Bowley productivity indicator based on the work of Bennet (1920) in the context of cost of living and Bowley (1928) in the welfare context. See Chambers (2001, 2002) who shows how exact and superlative productivity indicators can be computed as Bennet–Bowley measures of profit differences. Note that Chambers also refers to the Bennet cost indicator as the Bennet–Bowley cost measure.

[4] As pointed out by Diewert (2005, p. 342) a nice feature of the Bennet indicators of price and volume change is their additive property over commodities which give them 'a big advantage' over their superlative counterparts (e.g. Fisher or Törnqvist) which are inherently non-additive over commodities. The Montgomery (1929, 1937) indicators of price and volume change are also additive over commodities but their axiomatic or test properties are not as attractive as those of the Bennet indicators (see Diewert, 2005, p. 342).

[5] Of course there are ratio measures such as the Fisher index which are well defined irrespective of the signs or values of prices and quantities and difference measures such as the Montgomery indicator, which are not.

[6] Diewert (2005) compares and contrasts the Bennet indicator to other measures of value change, such as the Montgomery–Vartia indicator (see Montgomery, 1929, 1937; Vartia, 1976a, 1976b) which has a structure similar to the Bennet indicator but uses logarithmic averages rather than simple averages as weights. He concludes that from the viewpoint of the axiomatic or test approach to value change, the Bennet indicator is best albeit in practice there may not be much difference between them.

[7] Let $T$ be a technology $T = \{(x, y)$: $x$ can produce $y\}$and let $g_x \in R_{+}^{N}$, $g_x \neq 0$ be a directional vector. Then the directional input distance function is defined as $\vec{D}(x, y; g_x) = \sup\{\beta : (x - \beta g_x, y) \in T\}$. The Luenberger input indicator is defined as the average of a base period technology Luenberger input indicator $L^{o} = \vec{D}_1^{o}(x^{o}, y^{o}; g_x) - \vec{D}_1^{o}(x^{1}, y^{o}; g_x)$ and period-1 technology Luenberger input indicator $L^{1} = \vec{D}^{1}(x^{o}, y^{1}; g_x) - \vec{D}^{1}(x^{1}, y^{1}; g_x)$, see Chambers (2002, p. 757).

[8] Chambers (2002, p. 757) shows that if the firm minimizes cost, and the directional input distance function is quadratic and satisfies the translation property, the Bennet cost measure is "a superlative input indicator in the sense that it is an exact measure for a second order flexible representation of the technology." In addition, he shows the Bennet cost measure calculated using input prices normalized by the value of the directional vector is "an exact input indicator regardless of whether the technology exhibits constant returns to scale and regardless of whether the entities involved choose outputs optimally." An intuitive choice to use in this normalization would be $g_x = \bar{x}$, which would result in normalizing input prices by the value of the input bundle evaluated at the mean of the input data; i.e. the sample means of capital, land, labor, fertilizers, pesticides and energy use in each state.

Our data set consists of $k = 1,\ldots, K\ (=48)$ states, where we denote each state's cost at time $\tau$ by $C_k^\tau$. Thus the aggregate cost is

$$C^\tau = \sum_{k=1}^{K} C_k^\tau. \tag{6}$$

We define the aggregate cost difference as

$$C^{t+1} - C^t = \sum_{k=1}^{K} C_k^{t+1} - \sum_{k=1}^{K} C_k^t \tag{7}$$

and note that

$$\sum_{k=1}^{K} C_k^{t+1} - \sum_{k=1}^{K} C_k^t = \sum_{k=1}^{K} (C_k^{t+1} - C_k^t). \tag{8}$$

Thus the aggregate cost difference between adjacent periods equals the difference in the sum of sub-aggregate changes. Also note that

$$\sum_{k=1}^{K} (C_k^{t+1} - C_k^t) = \sum_{k=1}^{K} (W_{k,t}^{t+1} + X_{k,t}^{t+1}) = \sum_{k=1}^{K} W_{k,t}^{t+1} + \sum_{k=1}^{K} X_{k,t}^{t+1} \tag{9}$$

where $W_{k,t}^{t+1}$ and $X_{k,t}^{t+1}$ denote the $k$s price and volume (quantity) indicator, respectively, and their sums are the aggregate indicator.

Kevin Fox (2006, p. 75) summarizes the aggregation property of the Bennet indicator as: '…what holds for a one-good context holds for a many-good context, as the many-good context is simply the sum of the one-good contexts.' As we have seen, the same applies to the states that make up the aggregate indicator.

The second objective of this paper is to study productivity, especially energy productivity, which is a partial productivity measure much like the familiar labor productivity index. Our approach, again, is based on indicator theory, i.e., we employ differences rather than the ratio form of the energy productivity index.

To measure productivity or productivity change, we begin by looking at the change in profit

$$\Pi^{t+1} - \Pi^t = \left(R^{t+1} - C^{t+1}\right) - \left(R^t - C^t\right) \tag{10}$$

where

$$R^\tau = p^\tau y^\tau = \sum_{m=1}^{M} p_m^\tau y_m^\tau, \quad \tau = t, t+1, \tag{11}$$

is the revenue at time $\tau$, $p^\tau \in R_+^M$ denotes output prices, and $y^\tau \in R_+^M$ denotes the associated output quantities.

As in the case of costs, revenue change

$$R^{t+1} - R^t \tag{12}$$

can be decomposed into price and volume components

$$R^{t+1} - R^t = P_t^{t+1} + Y_t^{t+1} \tag{13}$$

where

$$P_t^{t+1} = \frac{1}{2}\left(y^{t+1} + y^t\right)\left(p^{t+1} - p^t\right) \tag{14}$$

and

$$Y_t^{t+1} = \frac{1}{2}\left(p^{t+1} + p^t\right)\left(y^{t+1} - y^t\right). \tag{15}$$

Again, the average of the output quantities serves as the weight for the change in output prices and the average of the output prices serves as the weight for the volume change indicator. As suggested by Chambers (2002, p. 759) a normalized revenue indicator can be obtained by deflating prices by the value of the direction vector. This normalization comes naturally from the duality between the revenue function and the directional output distance function $\vec{D}\left(x, y; g_y\right) = \sup\left\{\beta : \left(x, y + \beta g_y\right) \in T\right\}$. An intuitive choice to use in this normalization would be $g_y = \bar{y}$, which would result in normalizing output prices by the value of the output bundle evaluated at the mean of the output data; i.e. the sample means of crops, livestock and other farm related output in each state.

Putting our cost change and revenue change indicators together our change in profit may be rewritten as:

$$\begin{aligned} \Pi^{t+1} - \Pi^{t+1} &= \left(R^{t+1} - C^{t+1}\right) - \left(R^t - C^t\right) \\ &= \left(R^{t+1} - R^t\right) - \left(C^{t+1} - C^t\right) \\ &= P_t^{t+1} + Y_t^{t+1} - W_t^{t+1} - X_t^{t+1} \\ &= \left(P_t^{t+1} - W_t^{t+1}\right) + \left(Y_t^{t+1} - X_t^{t+1}\right). \end{aligned} \tag{16}$$

The first expression on the last line, $(P_t^{t+1} - W_t^{t+1})$, describes the 'price' component of profit change. The second expression $(Y_t^{t+1} - X_t^{t+1})$ captures the 'real profit' or productivity change component. This expression is also known as the Bennet–Bowley productivity indicator (BB), named after Bennet (1920) and Bowley (1928). Note that if there is no change in prices, total profit change will be embedded in the 'real' productivity component.

Again our data consist of $k = 1,\ldots, K\ (=48)$ states; denoting each state's revenue at time $\tau$ as $R_k^\tau$, the aggregate revenue is $R^\tau = \sum_{k=1}^{K} R_k^\tau$. Thus our expression for change in profit may be written in aggregate form as the sum over states of the components, i.e.

$$\begin{aligned} \left(R^{t+1} - C^{t+1}\right) - \left(R^t - C^t\right) &= \sum_{k=1}^{K} (R_k^{t+1} - R_k^t) - \sum_{k=1}^{K} (C_k^{t+1} - C_k^t) \\ &= \sum_{k=1}^{K} (P_{k,t}^{t+1} - W_{k,t}^{t+1}) - \sum_{k=1}^{K} (Y_{k,t}^{t+1} - X_{k,t}^{t+1}) \\ &= \left(P_t^{t+1} - W_t^{t+1}\right) + \left(Y_t^{t+1} - X_t^{t+1}\right). \end{aligned} \tag{17}$$

Thus the aggregate change in profits also decomposes into a price change component

$$P_t^{t+1} - W_t^{t+1} = \sum_{k=1}^{K} (P_{k,t}^{t+1} - W_{k,t}^{t+1}) \tag{18}$$

and a volume or quantity component

$$Y_t^{t+1} - X_t^{t+1} = \sum_{k=1}^{K} (Y_{k,t}^{t+1} - X_{k,t}^{t+1}). \tag{19}$$

As mentioned before, for these indicators to make sense, the prices must be 'deflated' by some general measure, which following Chambers (2002) is defined to be the total value of the input and output bundles evaluated at the mean of the input and output data, respectively, in each state.[9] Thus the normalized profit indicator is expressed as:

$$\tilde{\Pi}^{t+1} - \tilde{\Pi}^t = \frac{\Pi^{t+1}}{w^{t+1}\bar{x} + p^{t+1}\bar{y}} - \frac{\Pi^t}{w^t\bar{x} + p^t\bar{y}} \tag{20}$$

[9] Chambers (2002, p. 760) shows that if the firm maximizes profit, and the technology directional distance function is quadratic and satisfies the translation property, then "exact and superlative productivity indicators can be computed as Bennet–Bowley measures of profit difference." He suggests that a normalized profit indicator can be obtained by deflating prices by the total value of the direction vector. This normalization comes naturally from the duality between the profit function and the directional distance function $\vec{D}\left(x, y; g_x, g_y\right) = \sup\left\{\beta : \left(x - \beta g_x, y + \beta g_y\right) \in T\right\}$. An intuitive choice to use in this normalization would be $\left(g_x, g_y\right) = (\bar{x}, \bar{y})$ which would result in normalizing prices by the total value of the input–output bundle evaluated at the mean of the input–output data.

The normalized Bennet–Bowley quantity change indicator is then given by:

$$BB^{t+1} = \frac{1}{2}\left(\frac{p^{t+1}}{w^{t+1}\overline{x} + p^{t+1}\overline{y}} + \frac{p^t}{w^t\overline{x} + p^t\overline{y}}\right)\left(y^{t+1} - y^t\right) - \frac{1}{2}\left(\frac{w^{t+1}}{w^{t+1}\overline{x} + p^{t+1}\overline{y}} + \frac{w^t}{w^t\overline{x} + p^t\overline{y}}\right)\left(x^{t+1} - x^t\right) \tag{21}$$

And the normalized price change indicator as:

$$\widetilde{P}^{t+1} = \frac{1}{2}\left(y^{t+1} + y^t\right)\left(\frac{p^{t+1}}{w^{t+1}\overline{x} + p^{t+1}\overline{y}} - \frac{p^t}{w^t\overline{x} + p^t\overline{y}}\right) - \frac{1}{2}\left(x^{t+1} + x^t\right)\left(\frac{w^{t+1}}{w^{t+1}\overline{x} + p^{t+1}\overline{y}} - \frac{w^t}{w^t\overline{x} + p^t\overline{y}}\right) \tag{22}$$

with the property that

$$\widetilde{\Pi}^{t+1} - \widetilde{\Pi}^t = BB^{t+1} + \widetilde{P}^{t+1}. \tag{23}$$

In our empirical section on productivity, instead of total cost we will focus on energy cost, so that we obtain a partial rather than a total factor productivity indicator. This means that the cost, input price and quantity variables are specific to energy which allows us to decompose revenue change due to a change in energy cost into a partial price and a partial productivity component. Since costs are additive, the total factor productivity (TFP) indicator is simply the difference between an output quantity indicator and the sum of the individual input quantity indicators (see also Balk, 2010).

## 3. The data

This section provides a brief overview of our data. A more detailed description of the sources and methods can be found in Ball et al. (1999, 2004, 2012). The accounts for each state are derived from a panel of annual observations. State-specific aggregates of output and capital, labor, and materials inputs are formed as Törnqvist indexes over detailed output and input accounts. Törnqvist output indexes are formed by aggregating over agricultural goods and services using revenue-share weights based on shadow prices which are inclusive of government payments.[10] Data on hours worked and compensation per hour cross-classified by demographic characteristics of the agricultural labor force underpin our estimates of labor input.

To construct a measure of capital input, we require data on the capital stock for each component of capital input. Estimates of depreciable capital are derived by representing capital stock at each point of time as a weighted sum of all past investments. The weights correspond to the relative efficiencies of capital goods of different ages, so that the weighted components of capital stock have the same efficiency.[11] The stocks of land and inventories are measured as implicit quantities derived from balance sheet data. Indexes of capital input are formed by aggregating over the various capital assets using cost-share weights based on asset-specific rental prices. The derivation of the capital rental prices is discussed in Ball et al. (2008).

Törnqvist indexes of energy consumption are calculated for each state by weighting the growth rates of petroleum fuels, natural gas, and electricity by their value shares in the overall value of energy inputs. Fertilizers and pesticides are also important intermediate inputs. But these inputs have undergone significant changes in quality over the study period. To account for changes in input quality, price indexes for fertilizers and pesticides are constructed using hedonic methods. A price index for fertilizer is obtained by regressing prices of single nutrient and multigrade fertilizer materials on the proportion of nutrients contained in the materials; prices for pesticides are regressed on differences in physical characteristics such as the chemical's potency, toxicity, persistence in the environment, and leaching potential.[12]

The corresponding quantity indexes for fertilizers and pesticides are formed implicitly by taking the ratio of the value of each aggregate to its hedonic price index. Finally, indexes of output and input prices in each state relative to those in a numeraire state were constructed for the base year, 1996.[13] We have compiled price indexes for each state for the period 1960–2004. Price indexes in each state relative to those in the numeraire state for each year were obtained by linking the time-series price indexes with the estimates of relative prices in the base year. The indexes of relative prices were used to construct estimates of the levels as well as growth rates of the output and input aggregates.[14]

## 4. Energy cost

In this section we look at the development of energy costs in the U.S. agricultural sector over the time period 1960–2004. We apply the Bennet indicator discussed in Section 2. Specifically we focus on the price and volume (quantity) components.

Recall that the cost change may be written as $C^{t+1} - C^t = W_t^{t+1} + X_t^{t+1}$, where $W_t^{t+1}$ is the price indicator and $X_t^{t+1}$ is the volume (quantity) indicator. In our empirical analysis we have used data on petroleum fuels, gas and electricity to construct the Bennet energy cost

[10] Note that we take the subaggegate index series for inputs and outputs as given and we combine them to form aggregate value indices and their decomposition into measures of aggregate price change and quantity change. Next we use a similar approach to aggregate at a lower level, i.e. at the level of a specific input such as energy, and as such obtain a partial value change indicator along with its decomposition into a price change and quantity change measure.

[11] A detailed description of the methods used to construct the capital stocks is provided in Ball et al. (2008). The "relative efficiency" of assets as they age is given by a hyperbolic decay function concave to the origin. Asset service life is assumed to be a normally distributed random variable and relative efficiencies are calculated for each of the possible service lives. An aggregate efficiency function is then constructed as the weighted sum of the individual efficiency functions where the weights are the probabilities of occurrence. The resulting aggregate efficiency function reflects both loss of efficiency as the asset ages and discards of worn out assets. The time series on investment is sufficiently long to allow the use of a zero benchmark for the initial period capital stock which dates back to 1871. Given assumptions of a mean service life of 38 years and tail service life of 76 years under normally distributed discards, any investment prior to 1871 will be fully "replaced" by 1947.

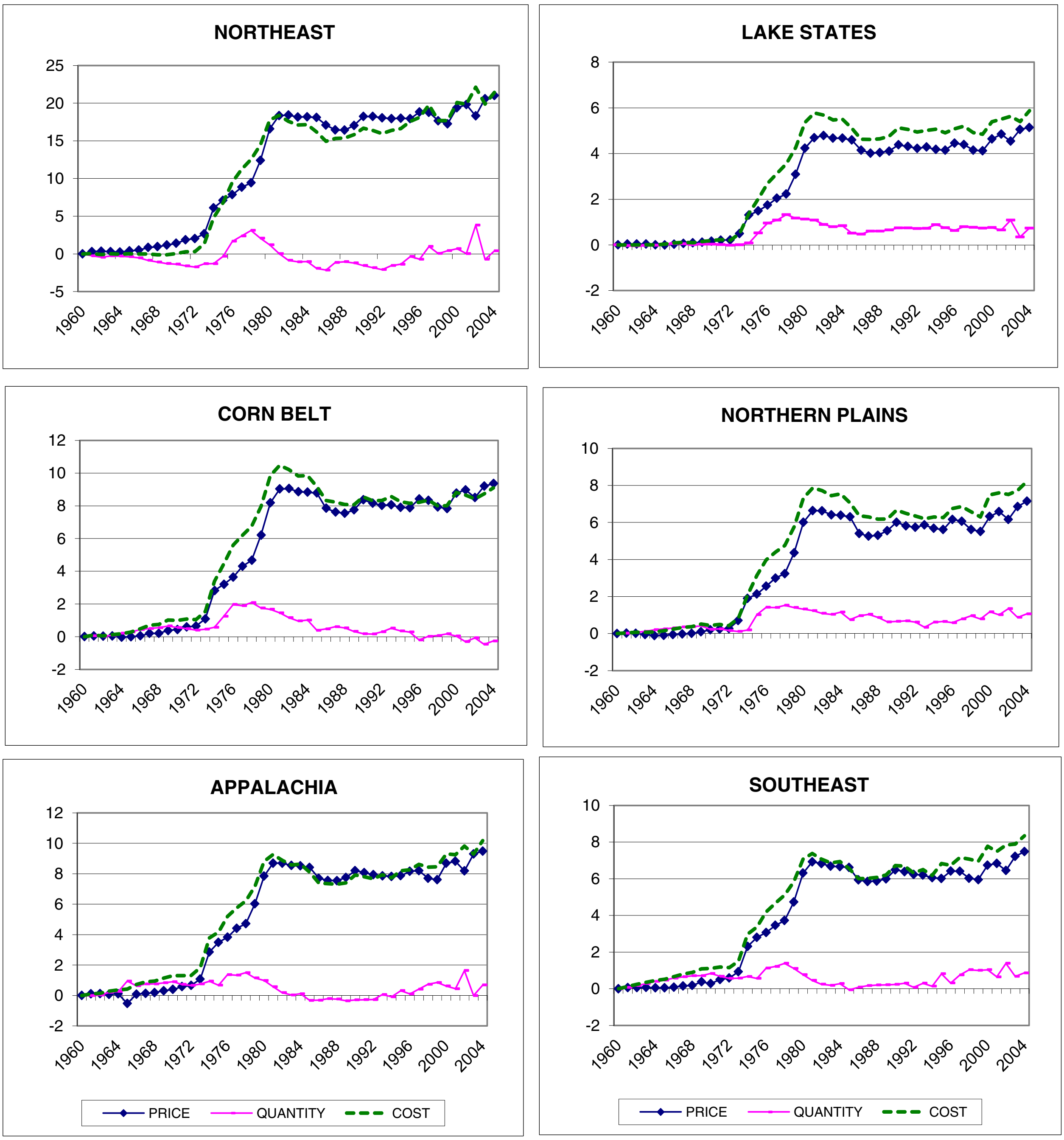
[12] The following characteristics are included in the hedonic regression: application rate, chronic score, half-life, sorption, water solubility and vapor pressure. These characteristics reflect the chemical's potency (application rate), toxicity (chronic score), persistence in the environment (half-life and sorption), and leaching potential (water solubility and vapor pressure). The application rate measures the chemical's potency. Hazardous characteristics are measured by chronic toxicity scores, and persistence is measured by the pesticide's half-life. The chronic toxicity index is the inverse of the water quality threshold (which measures the concentration in parts per billion) and serves as an indicator for environmental-risk. The lower the index, the lower is the potential environmental risk for the chemical. The persistence indicator is defined by the share of pesticides with a half-life less than 60 days (the lower the indicator, the less persistent the pesticide is) and by the degree to which the pesticide binds to soil particles (sorption coefficient Koc). The leaching potential is measured by the water solubility (measured as the amount in milligrams of pesticides that would dissolve in 1 L of water, mg/L) and vapor pressure (how readily a chemical will evaporate) measured in millimeters of mercury (mm Hg).

[13] Like the multilateral versions of the Fisher and Tornqvist indexes, the multilateral Bennet indicator compares the price of, say diesel fuel, in a given state to the mean price across all states. This is necessary in order to obtain a measure which is both intertemporally and interspatially consistent. To express the results relative to a base state (i.e., Alabama), we simply subtract the "indicator" for Alabama relative to the mean from the indicators for Arkansas, Arizona, etc. The results are invariant to the choice of the numeraire state. This ensures our calculations are base-state invariant. To obtain a base-year invariant measure, we use 1996 as a base year and we construct our indexes for earlier and later years in the sample by chain linking them to 1996. The result is a 'true' panel with both temporal and spatial comparability. See Ball et al. (2004) for further discussion.

[14] Updates of the state-level statistics have been suspended in light of reduced USDA Economic Research Service (ERS) resources and the discontinuance of key sources of data series. While more up-to-date data would have been desirable, this does not detract attention from the main interest of our analysis focussing on the 1970s major oil price shocks that resulted in a rapid and unexpected rise in energy prices and their aftermath linked to a slowdown in U.S. agricultural productivity growth (see Ball et al., 2013).

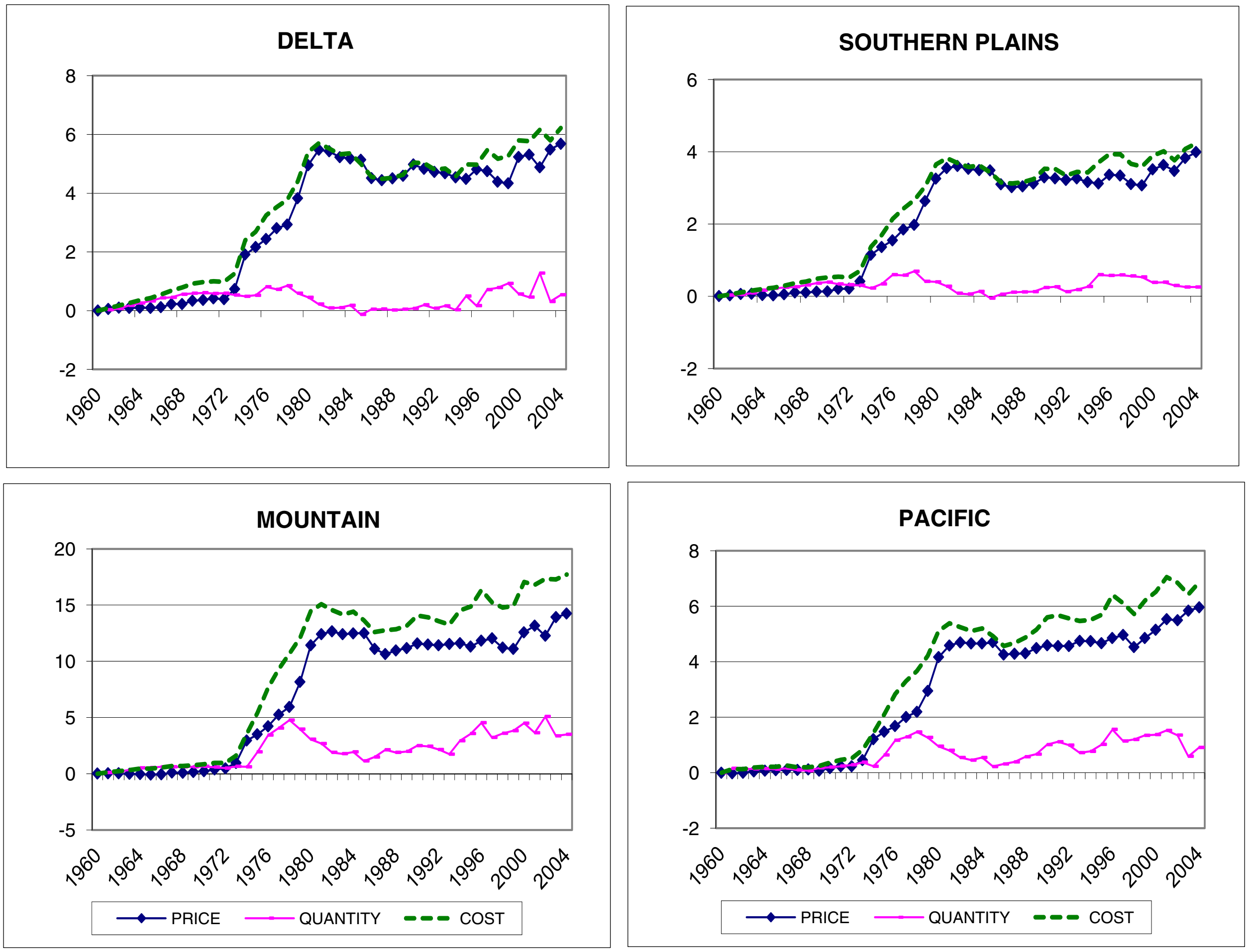
indicator and decompose it into price and quantity change. The energy cost indicator is deflated by the value of the fuels, gas and electricity bundle evaluated at the sample average of these quantities.

Fig. 1 shows the time paths of the energy cost indicator and its price and quantity components for the 10 U.S. farm production regions during the period 1960 to 2004. It is clear from these plots that energy costs




NORTHEAST (Connecticut, Delaware, Maryland, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont);
LAKE STATES (Michigan, Minnesota, Wisconsin);
CORN BELT (Illinois, Indiana, Iowa, Missouri, Ohio);
NORTHERN PLAINS (Kansas, Nebraska, North Dakota, South Dakota);
APPALACHIAN (Kentucky, North Carolina, Tennessee, Virginia, West Virginia);
SOUTHEAST (Florida, Georgia, Alabama, South Carolina)

**Fig. 1.** Energy cost indicators.




DELTA (Arkansas, Louisiana, Mississippi);
SOUTHERN PLAINS (Oklahoma, Texas);
MOUNTAIN (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming;
PACIFIC (California, Oregon, Washington)

**Fig. 1** (*continued*).

track very closely increases in energy prices with very little contribution from changes in energy use.[15] Overall direct energy use appears to be increasing until the mid-1970s, declines over the next decade, and starts to rise again from the mid-1980s until about the late 1990s. This is similar to the direct energy use pattern reported by Miranowski (2005). There is a steep rise in energy costs across all regions during the 1970s oil price shocks starting with the oil embargo in 1973 and reaching a peak in the early 1980s following the 1978 Iranian revolution. Energy costs in most regions decline during the 1980s reaching a trough during the OPEC price-cutting war in 1986–1987, but they start to rise again following new waves of oil shocks associated with the Gulf War in the early 1990s, a price blip in the late 1990s, the 2001 terrorist attack in the U.S. and the 2002 run-up to the U.S. invasion of Iraq but at a much more moderate rate.

Analysis of the individual states reveals a positive and fairly substantial average annual rate of energy cost increase. The median rate of energy cost change during the 1960–2004 period was 4.63% per year, with farmers in 10 of the 48 states facing energy cost increases averaging more than 5% per year. Average annual rates of energy cost change ranged from 3.59% for Rhode Island to 6.08% for Delaware.

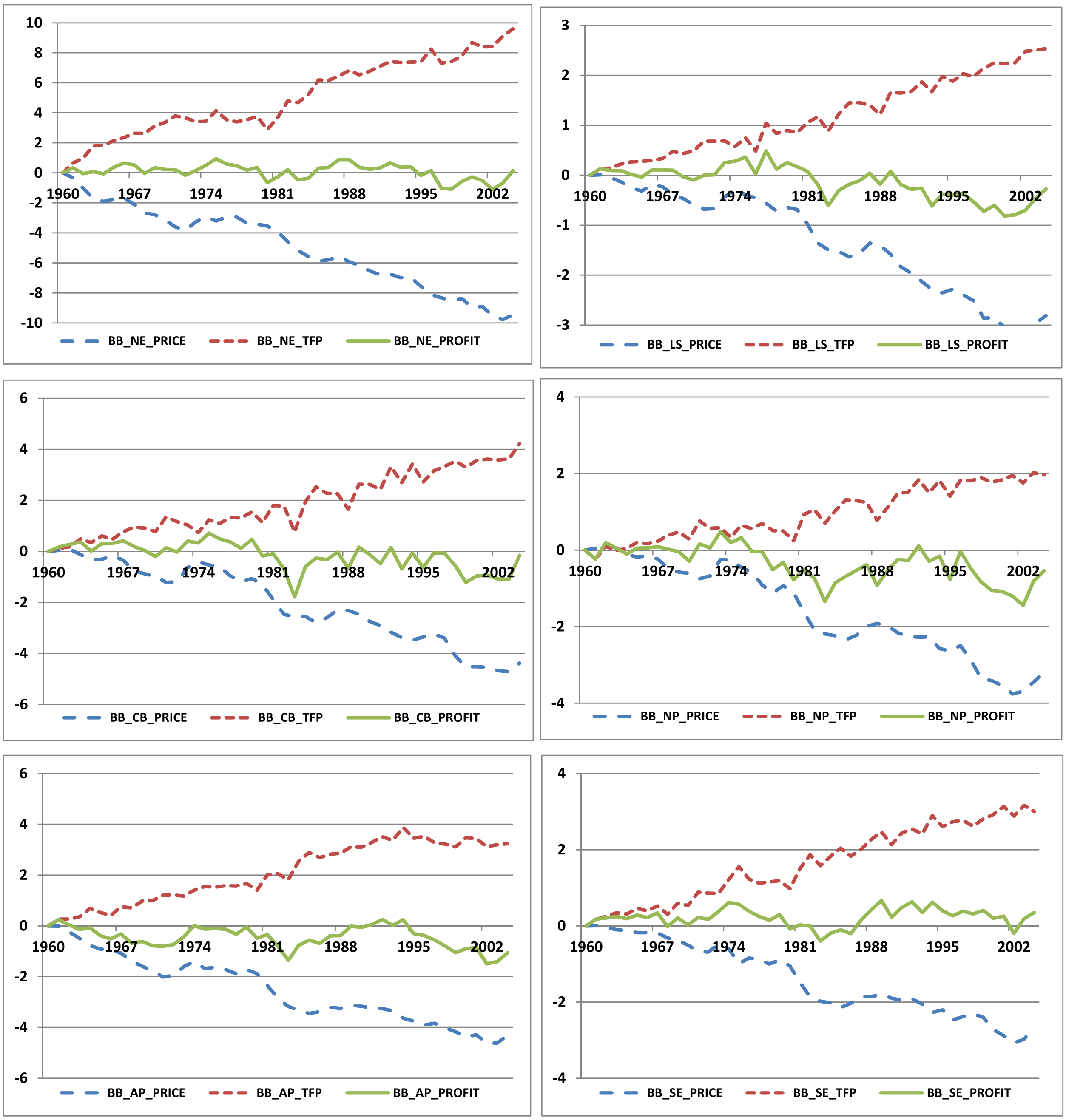
## 5. Energy and productivity

Energy productivity is the topic of this section. We apply the Bennet–Bowley indicator discussed in Section 2. Specifically we study the decomposition of profit change into price and productivity changes as described in Eq. (16). We provide both the partial energy productivity indicator as well as the total factor productivity (TFP) indicator. As shown in the Appendix (Tables A1), standard panel unit root tests provide no evidence of a unit root in the profit indicator across U.S. states or

[15] Our results show close correspondence between the Törnqvist energy price and implicit quantity indices and the Bennet indicator of energy price change and quantity change.

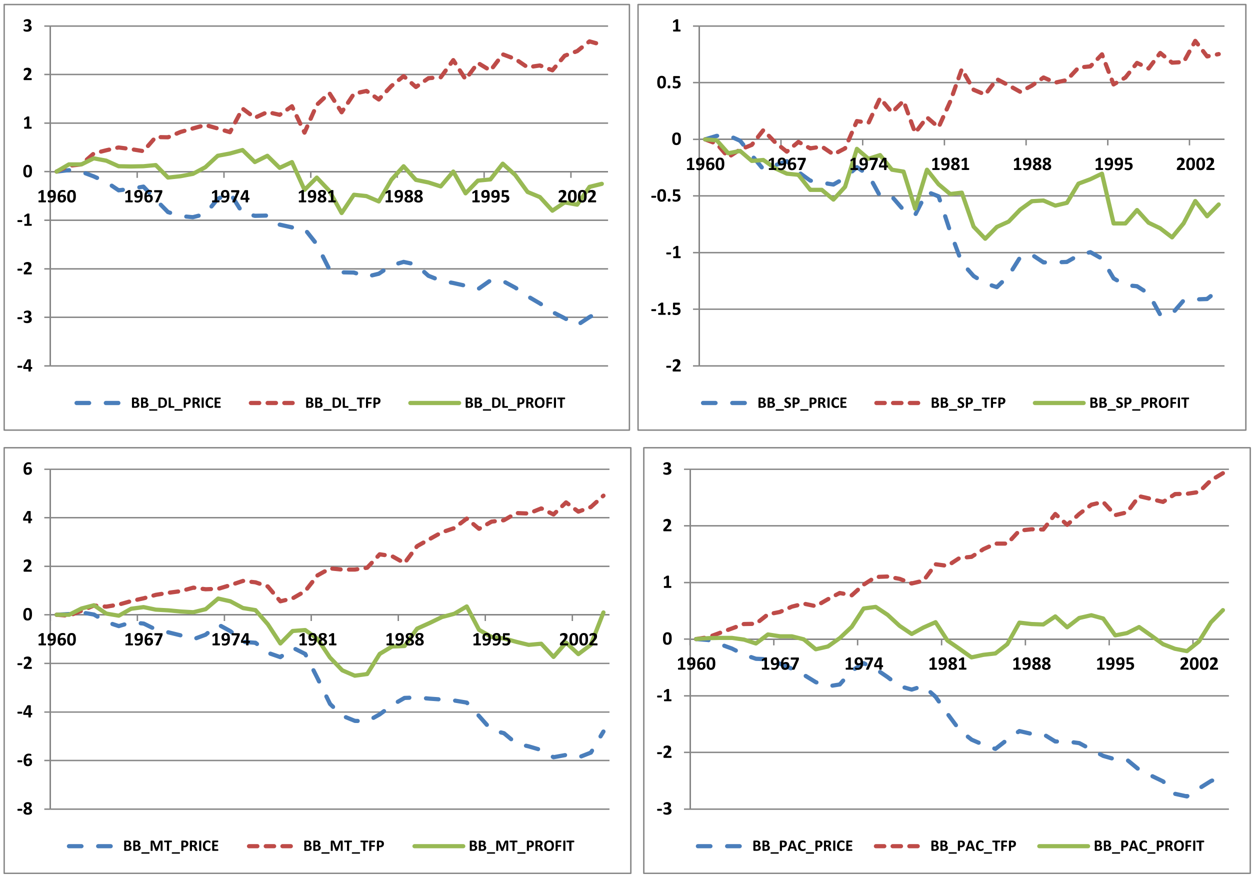
in the price and quantity components of the indicator. Also, as shown in Table A2, we find no evidence of a unit root in the energy productivity indicator.

Fig. 2 shows time plots of the profit change indicator (a measure of farm prosperity) and its components, the Bennet–Bowley productivity (TFP) indicator and the (normalized) price change indicator. The price




**NE** = NORTHEAST (Connecticut, Delaware, Maryland, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont);
**LS** = LAKE STATES (Michigan, Minnesota, Wisconsin);
**CB** = CORN BELT (Illinois, Indiana, Iowa, Missouri, Ohio);
**NP** = NORTHERN PLAINS (Kansas, Nebraska, North Dakota, South Dakota);
**AP** = APPALACHIAN (Kentucky, North Carolina, Tennessee, Virginia, West Virginia);
**SE** = SOUTHEAST (Florida, Georgia, Alabama, South Carolina)

**Fig. 2.** Bennet–Bowley profit, TFP and price indicators.




**DL** = DELTA (Arkansas, Louisiana, Mississippi);
**SP** = SOUTHERN PLAINS (Oklahoma, Texas);
**MT** = MOUNTAIN (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming;
**PAC** = PACIFIC (California, Oregon, Washington)

**Fig. 2** (*continued*).

indicator is the difference between the output price indicator, i.e. an aggregate measure of prices received by U.S. farmers, and the input price indicator, i.e. an aggregate measure of prices farmers paid for inputs. Following a sharp price increase in the early 1970s farm prices decline in real terms and especially if compared to input prices as shown in Fig. 2.[16] There is a clear contrast between the productivity indicator which displays a positive trend and the price indicator displaying a negative trend over time.

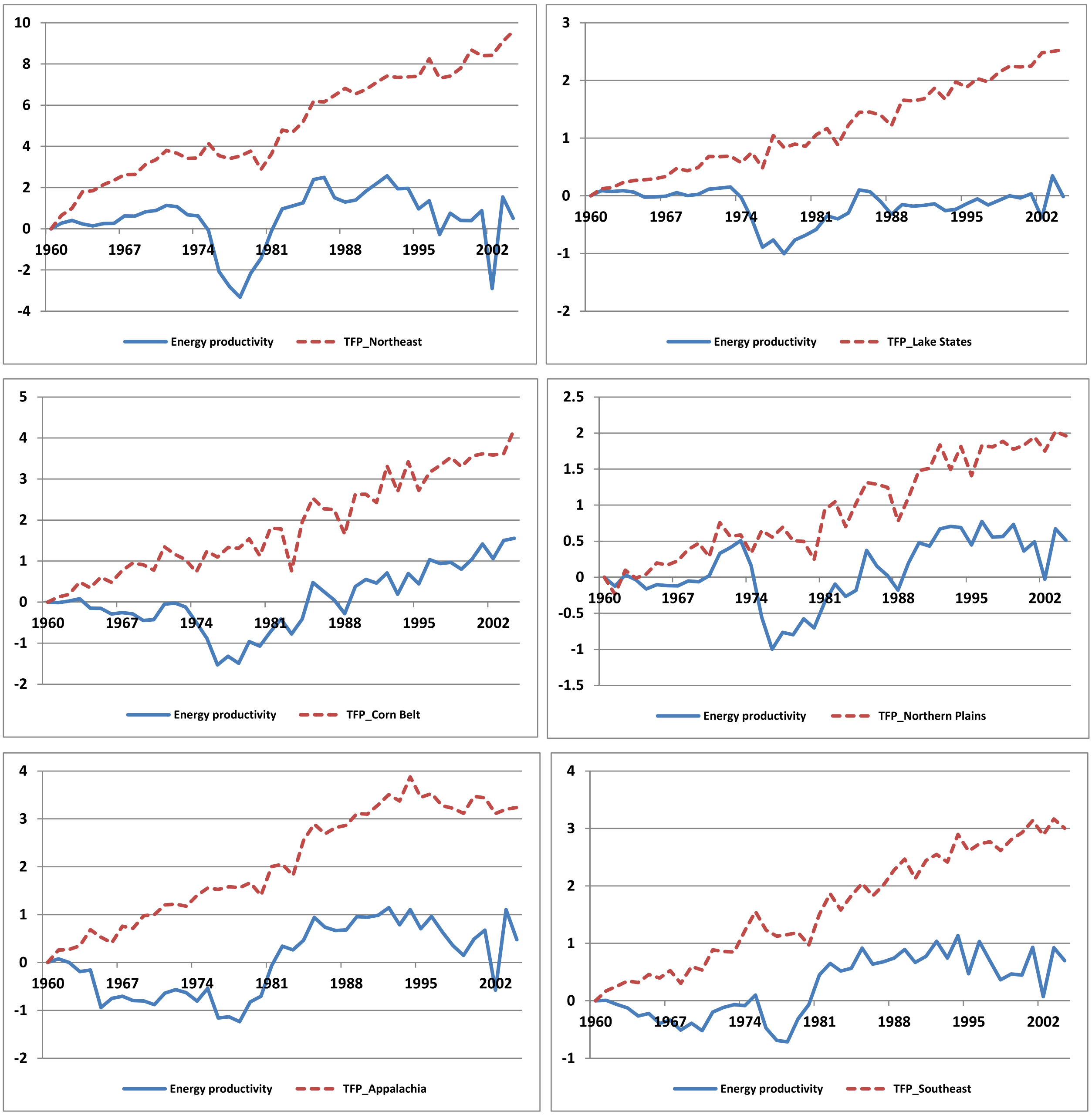
Every state shows a positive and generally substantial average annual rate of TFP growth. There is considerable cross-sectional variance, however. The median TFP growth rate over the 1960–2004 period was 1.76% per year.[17] However, 13 of the 48 states had productivity growth rates averaging more than 2% per year. Only Oklahoma and Wyoming had average annual rates of growth less than 1% per year. Average annual growth rates ranged from 0.56% for Oklahoma, 0.64% for Wyoming, and 1.05% for Tennessee to 2.46% for Massachusetts and Oregon, and 2.81% for Rhode Island. Profit change for most regions hovers around or just below zero.[18] Notable exceptions displaying negative profitability are the Northern Plains, Delta, Mountain and Southern Plains regions. But these regions exhibited relatively modest gains in productivity. Our results show that 22 of the 48 states had negative average profit change rates, with Louisiana and Oklahoma reporting the lowest average annual rates at −0.89% −0.82%, respectively. Overall we find that the contributions of the price and quantity change components are largely offsetting, with the long term trend in profitability of the U.S. farm sector being very nearly flat.

[16] The Bennet–Bowley output price indicator declines by an average annual rate of 1.3% between 1974 and 1978 while the output indicator increases at a rate of 2.5% per annum during the same period. The highest output increases are reported in Iowa (5.4%), Indiana (5.7%), Arkansas (6.1%), Illinois (6.2%), and North Dakota (8.2%) on average per year.

[17] This is slightly above the median state TFP growth rate reported by USDA (see http://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us/findings,-documentation,-and-methods.aspx#ball2010) using the Törnqvist index. In general, TFP growth rates are slightly higher under the Bennet–Bowley compared to the Törnqvist measure.

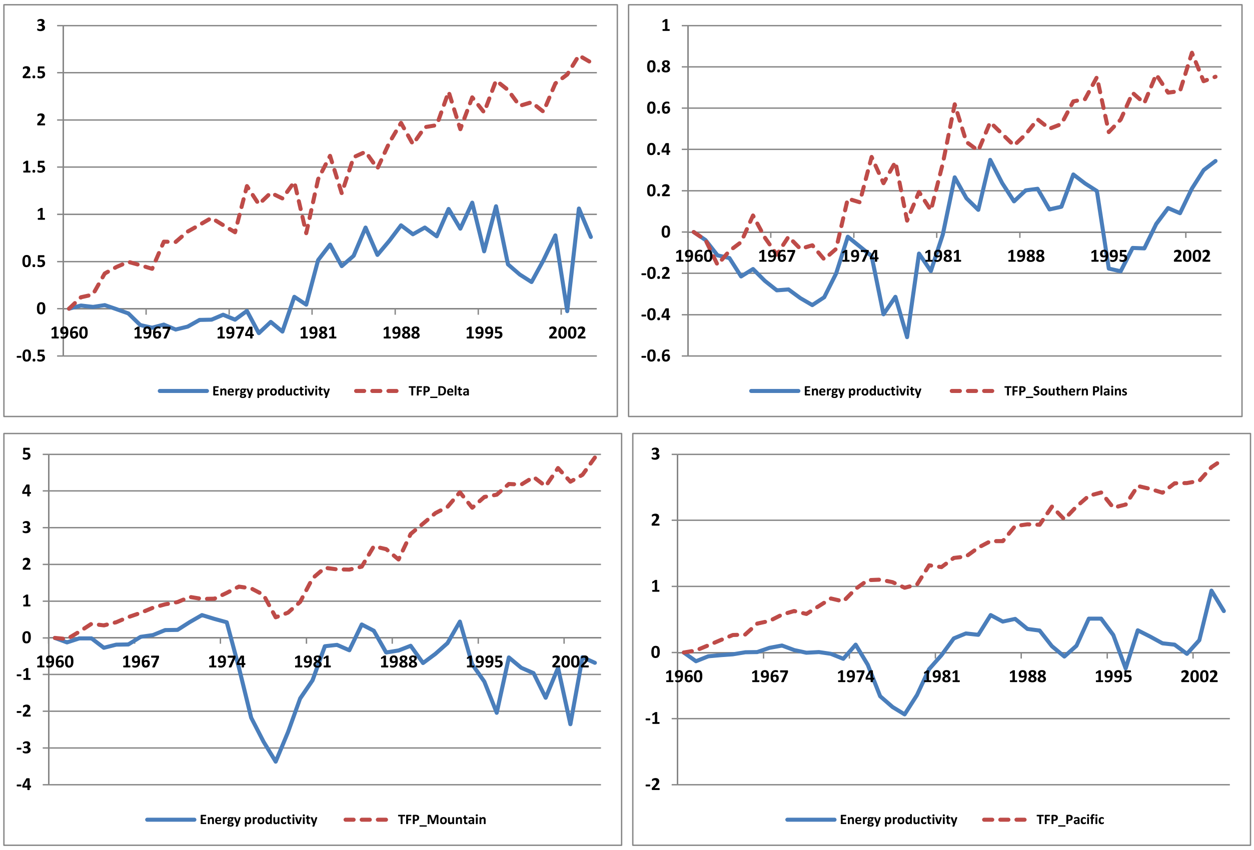
[18] Ball et al. (2010) report a positive relationship between productivity and R&D expenditure in the U.S. agricultural sector. They also report a negative trend in the price indicator suggesting that the benefits of public R&D expenditures accrue largely to the consumer through lower real prices.

Fig. 3 shows time plots of the partial (energy) productivity indicator in comparison to the TFP indicator. Energy productivity is more volatile than total factor productivity and in most cases falls well short of the rate of change in TFP which appears to be positive and substantial during most of the period. Some notable exceptions are the Northern Plains, Delta and Southern Plains regions where energy productivity tracks TFP very closely from 1980 to 1996. There is a widening gap between energy productivity and TFP in the Northeast, Lake States and




NORTHEAST (Connecticut, Delaware, Maryland, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont);
LAKE STATES (Michigan, Minnesota, Wisconsin);
CORN BELT (Illinois, Indiana, Iowa, Missouri, Ohio);
NORTHERN PLAINS (Kansas, Nebraska, North Dakota, South Dakota);
APPALACHIAN (Kentucky, North Carolina, Tennessee, Virginia, West Virginia);
SOUTHEAST (Florida, Georgia, Alabama, South Carolina)

**Fig. 3.** TFP and energy productivity indicators.




DELTA (Arkansas, Louisiana, Mississippi);
SOUTHERN PLAINS (Oklahoma, Texas);
MOUNTAIN (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming;
PACIFIC (California, Oregon, Washington)

**Fig. 3** (*continued*).

Mountain regions. Energy productivity did recover in the 1980s but not as fast as TFP. Our findings corroborate previous results—see Cleveland (1995) who reports a shift in the productivity of energy use in the U.S. agriculture during the 1980s. In particular, he reports a decrease in energy productivity in the 1960s and 1970s driven by diminishing returns to energy use per hectare of land, associated with a sharp increase in the quantity of land harvested from 1968 to 1978; and an increase in energy productivity in the 1980s which he attributes to a decrease in energy use per hectare coupled with a reduction in cropland, and continuing improvements associated with increasing farm size. He concludes that these productivity gains reflect the adoption of better technologies and farm management techniques as a response to rising energy price pressures.

Next we proceed to analyze the effect of input and output prices on profitability using panel regressions. We report cluster adjusted fixed effects panel estimates for the profit change indicator in Table 1. We find that the energy price has a negative effect on farm profitability. Similarly, land and labor costs are negatively related to profitability while output prices for crops and livestock have a positive effect on farm profits. A surprising result is that the price of pesticides is positively related to profit change although the effect is not statistically significant. One possibility is that this finding can be explained by quality change which has not been captured fully by the hedonic adjustment method used to construct the pesticides price measure. We have controlled for weather and specialization using an index of total precipitation between March and August and the Hirschmann–Herfindahl index of specialization, respectively.[19] We find that precipitation has a positive effect on profitability. The effect of specialization is also positive.

Table 2 presents Arellano–Bond (1991) dynamic panel estimates for the Bennet–Bowley productivity change (TFP) indicator. As shown in Fig. 3, energy productivity shows much greater fluctuation than total productivity. The panel estimates indicate that while there is an overall positive adjustment of total productivity to energy productivity change, the intermediate response appears to be negative.[20] A possible explanation for this finding is offered by Ball et al. (2013). They argue that the

[19] The Hirschman–Herfindahl index of specialization is constructed as the sum of squares of the output shares in total output. As such, it can range from 0 to 1.0, moving from a large number of goods, each representing a small share of total output, to production of a single output. See Hirschman (1964).

[20] The long-run energy coefficient estimate is 0.21 indicating that a change in energy productivity makes about one-fifth contribution to total farm productivity change.

**Table 1**
The impact of input and output prices on the profit indicator.

| Fixed effects panel estimator with robust standard errors adjusted for 10 regional clusters | | | | |
|---|---|---|---|---|
| Variable | Coef. | Std. Error | t-ratio | P > \|t\| |
| *Input prices* | | | | |
| P_energy | −0.1972 | 0.0343 | −5.7500 | 0.0000 |
| P_fertilizer | −0.0114 | 0.0404 | −0.2800 | 0.7840 |
| P_pesticides | 0.1175 | 0.0927 | 1.2700 | 0.2360 |
| P_land | −0.0432 | 0.0152 | −2.8500 | 0.0190 |
| P_capital | −0.0380 | 0.0591 | −0.6400 | 0.5360 |
| P_labor | −0.1334 | 0.0197 | −6.7800 | 0.0000 |
| *Output prices* | | | | |
| P_crops | 0.2065 | 0.0764 | 2.7000 | 0.0240 |
| P_livestock | 0.1150 | 0.0281 | 4.1000 | 0.0030 |
| P_other output | 0.1339 | 0.0770 | 1.7400 | 0.1160 |
| *Controls* | | | | |
| HHI | 0.5704 | 0.2078 | 2.7400 | 0.0230 |
| Prec | 0.0072 | 0.0023 | 3.1400 | 0.0120 |
| Constant | −0.2946 | 0.0534 | −5.5200 | 0.0000 |
| R-square | within | 0.3259 | | |
| | between | 0.0432 | | |
| | overall | 0.0437 | | |
| Number of obs. | 2160 | Groups | 48 | |

Notes:
PREC is total precipitation in inches between March and August.
HHI is the Hirschmann–Herfindahl index of specialization.

**Table 2**
The impact of energy productivity on the Bennet–Bowley TFP indicator.

| Arellano-Bond dynamic panel-data estimates with robust S.E.s | | | | |
|---|---|---|---|---|
| Variable | Coef. | Std. Error | t-Ratio | P > \|t\| |
| BB(−1) | 0.4792 | 0.0466 | 10.2798 | 0.0000 |
| BB(−2) | 0.2890 | 0.0354 | 8.1640 | 0.0000 |
| BB_Energy | 0.2001 | 0.0136 | 14.7668 | 0.0000 |
| BB_Energy(−1) | −0.1189 | 0.0197 | −6.0491 | 0.0000 |
| BB_Energy(−2) | −0.0649 | 0.0187 | −3.4780 | 0.0005 |
| BB_Energy(−3) | 0.0351 | 0.0090 | 3.8896 | 0.0001 |
| Log_R&D(−1) | 0.0347 | 0.0199 | 1.7389 | 0.0822 |
| HHI | 0.1838 | 0.0896 | 2.0509 | 0.0404 |
| Prec | 0.0002 | 0.0006 | 0.2707 | 0.7867 |
| Wald Chi-sq(9) | 6684.93 | p-value | 0.000 | |
| J-statistic | 42.09 | p-value | 0.338 | |
| Number of obs. | 1920 | Groups | 48 | |
| Arellano–Bond serial correlation test | | | | |
| Test order | m-Statistic | rho | SE(rho) | p-Value |
| AR(1) | −1.631 | −1.202 | 0.737 | 0.100 |
| AR(2) | −0.258 | −0.256 | 0.992 | 0.796 |

Notes:
BB is the Bennet–Bowley productivity change indicator.
BB_Energy is the Bennet–Bowley energy productivity change indicator.
Log_R&D is (log) public R&D expenditure.
PREC is total precipitation in inches between March and August.
HHI is the Hirschmann–Herfindahl index of specialization.
Wald Chi-square statistic tests the overall significance of the model.
J-statistic tests the null that the instruments as a group are exogenous.
The Arellano–Bond test for autocorrelation has a null hypothesis of no autocorrelation and is applied to the differenced residuals. The AR(1) test in first differences is expected to reject the null hypothesis. The AR(2) test in first differences is thus more important, since it detects autocorrelation in levels.

rapid and unexpected rise in energy prices in 1973 and again in 1979 accelerated the rate of obsolescence of the capital stock and simultaneously created opportunities for profitable new investment in more energy efficient equipment.[21] Since conventional measures of capital stock do not capture changes in the rate of obsolescence, this would at first appear as slower productivity growth. But rapidly expanding investment in equipment during the 1970s, both to replace obsolete capital stock and to expand output, led to a symmetric boost in both energy and total productivity during the 1980s.[22] Similarly, we find that investment in R&D has a positive effect on farm productivity although this effect is only significant at the 10% level. Finally, we control for the effects of weather and specialization. The effect of specialization on productivity is positive, as is March to August precipitation, but the latter effect is not statistically significant.

## 6. Conclusion

While agriculture is not a major energy user relative to other sectors of the economy, changes in energy costs can have a significant impact on farm profitability. Our analysis has shown that energy productivity has been volatile and has not in general been able to catch up with total factor productivity which shows a positive and generally substantial rate of growth. These findings suggest that there has been variable success in the response of farm production to changes in energy prices as well as to the ability of the farm sector to use energy more efficiently. The latter is important since energy efficiency plays a key role in developing sustainable agricultural practices in view of global pressures arising from population and income growth and an increasing trend towards urbanization.

[21] The recycling of "petrodollars" by the major oil exporting countries during the 1970s fueled rapid growth in demand for U.S. agricultural exports (in particular major row crops such as soybeans). Agricultural output increased at a rate faster than TFP over the same period and even faster than input use. The latter has generally been quite flat albeit input use did increase in the second half of the 1970s. Agricultural output prices increased, viz. more than doubled from 1972 to 1983, in nominal terms yet did not rise as fast as the U.S. general price index and not as fast as agricultural input prices—see Fuglie et al. (2007) for more information. Energy consumption did not decline in response to higher prices. In fact, a special board was established by the U.S. Government to ensure that agriculture got its fair share of the energy total. Agricultural exports kept the economy afloat and growth in export demand spurred output growth, and this output came about through increased fuel, capital, and chemicals inputs. Growth in both energy productivity and TFP slowed. But this was much more pronounced in energy productivity.

[22] Growth in TFP recovered dramatically during the 1980s, more so than energy productivity. This is visible in the Fig. 3 charts for most regions.

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