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Measurement of Output, Inputs, and Total Factor Productivity in U.S. Agricultural Productivity Accounts

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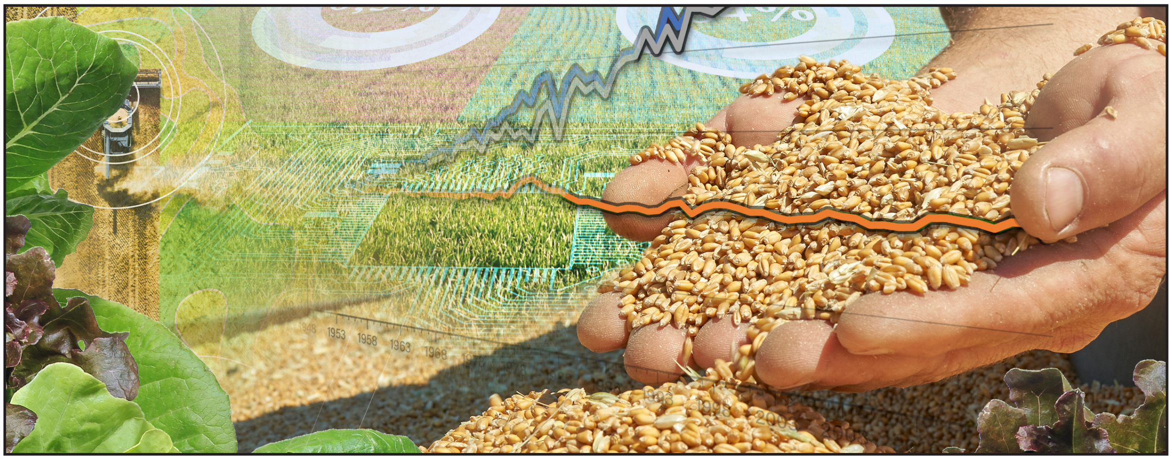

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Abstract

The U.S. Department of Agriculture (USDA) has been monitoring the U.S. farm sector's productivity performance since the 1960s. Today, USDA, Economic Research Service (ERS) bases its U.S. agricultural productivity statistics on a sophisticated system of production accounts, drawing data from numerous sources. A notable feature of the U.S. productivity accounts is the input quality adjustment, as some inputs have undergone significant changes in their quality over time. According to USDA, ERS estimates, between 1948 and 2021, total farm output grew by 1.46 percent annually. With total input declining by -0.03 percent per year on average, total factor productivity has become the primary driver in promoting output growth, increasing by 1.49 percent per year. Over time, the input composition has changed, shifting from labor and land use to more use of intermediate inputs (e.g., fertilizer, pesticides, and purchased services) and durable capital assets (e.g., tractors, combines, and other machinery). Input quality changes in labor, capital (including land), and intermediate inputs have contributed positively to annual output growth by 0.11, 0.04, and 0.04 percentage points, respectively.

Keywords: U.S. agriculture, input quality, quality-adjusted inputs, hedonic approach, index number approach, pesticides, fertilizer, purchased contract labor services, land, labor, capital, human capital, agricultural productivity, total factor productivity (TFP)

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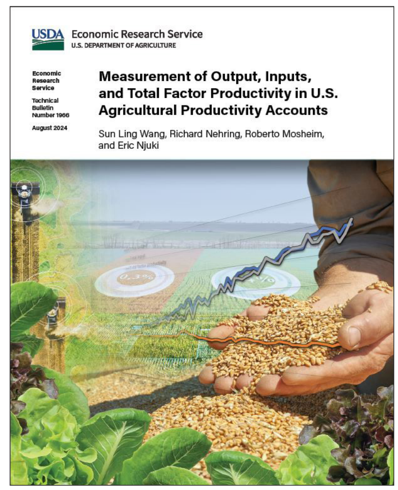


What Is the Issue?

This report addresses major issues on how USDA, ERS measures output, inputs, and TFP in its U.S. agricultural productivity accounts and how input quality changes are accounted for in the measurement. Agricultural productivity is an indicator that can provide information on the performance of the farm sector. Productivity can be measured by a single factor, like crop production per acre of land (crop yield). However, such measures can be misleading, as the measures can increase through additions to production inputs and not necessarily from technical improvement. In the 1960s, USDA, Economic Research Service (ERS) was the first agency to introduce the total factor productivity (TFP) measurement into the U.S. Federal statistical system. TFP measurement accounts for the use of all inputs under the farm operator's control. TFP growth is the difference between the growth of aggregate output and the growth of all inputs taken together. It measures changes in the efficiency with which inputs are transformed into outputs. However, input quality may change over time. It is necessary to measure inputs in their constant quality unit to avoid overstating the contribution of TFP to agricultural growth. Today, USDA, ERS bases its U.S. agricultural productivity statistics on a sophisticated system of production accounts. Input measures are adjusted for changes in their quality, such as improvements in the efficacy of chemicals or changes in the demographics of the farm workforce.

What Did the Study Find?

Productivity growth is the major driver of U.S. agricultural growth. Between 1948 and 2021, total U.S. farm output grew by 1.46 percent per year. With total inputs (including land, labor, capital, and intermediate inputs) declining slightly by -0.03 percent annually, total factor productivity grew at 1.49 percent per year, single-handedly driving farm output growth over the seven-decade period. In 2021, total farm output was about 2.9 times its 1948 level. Over time, the input composition has changed, shifting from labor and land to more usage of intermediate inputs and durable capital assets. During the period, input quality changes in labor, capital (including land), and intermediate inputs contributed positively to annual output growth by 0.11, 0.04, and 0.04 percentage points, respectively.

Fertilizers and pesticides have undergone significant changes in input quality. Over the decades, U.S. farmers have increasingly relied on intermediate inputs, such as chemical fertilizers and pesticides, in farm production. Fertilizers used in the U.S. agricultural production process include more than 50 different combinations of major fertilizer elements (nitrogen (N), phosphorus (P), and potassium (K)) and have undergone significant changes in quality over time. Pesticides have also altered their potency, persistence, toxicity, absorption rate, and application rate. USDA, ERS measures quality-adjusted prices and quantities for fertilizer and pesticide inputs. The results show that in 2019, the estimates of quality-adjusted and unadjusted fertilizer quantities were 2.5 times and 2 times (respectively) their 1948 level and 15 times and 8 times (respectively) for quality-adjusted and unadjusted pesticide quantities.

The quality of purchased contracted labor services has improved during the study period. USDA, ERS researchers estimated a wage function in terms of worker's years of farmwork experience, gender, educational attainment, language skill, legal status, and related controlled variables. The results show that estimated prices more than doubled in the last three decades. Among the six regions (see figure 6 for the list of regions), California ranked first in the relative level of quality-adjusted price of purchased contracted labor services in 1989, with the Southwest region ranking last. The Southwest region remained at the lowest level for more than 30 years, and the Northwest region's price surpassed California's and became the highest in 2019.

USDA, ERS has adopted an index number approach to measure quality-adjusted prices and quantities for labor and land in U.S. agricultural productivity accounts. With a composition shift among demographic characteristics (including age, educational attainment, gender, and employment type) labor quality has improved over time, contributing an average of 0.11 percentage points to output growth annually between 1948 and 2021. This contribution has been primarily due to higher educational attainment among workers. Land composition has shifted as well, with some higher-value land being reallocated to other uses. As a result, the measured land quality was reduced throughout the period, along with a land quantity reduction. In addition, urbanization and industrialization may have pulled away some more desirable farmland of better quality or with higher prices playing a role in the reductions.

How Was the Study Conducted?

USDA, ERS economists developed various models to measure quality-adjusted prices and quantities for various inputs in the U.S. agricultural productivity accounts. Researchers drew data from different sources, including published and unpublished data from Government statistical agencies and private sectors. Detailed sources of data are described in the box "Major Data Sources for the U.S. Agricultural Productivity Accounts" in the Introduction section.

Measurement of Output, Inputs, and Total Factor Productivity in U.S. Agricultural Productivity Accounts

Introduction

The growth of input use (labor, capital, materials, etc.) has been the primary source of growth for the U.S. aggregate economy and for most sectors since the end of World War II (Jorgenson et al., 2019). However, the farm sector is one of a few exceptions, with productivity growth being the major contributing factor to farm output growth (Jorgenson et al., 2019). Given the relevance of productivity growth to farm output growth, the U.S. Department of Agriculture (USDA) has been monitoring the farm sector's productivity performance for decades. In the 1960s, the USDA's Economic Research Service (ERS) was the first agency to introduce the multifactor productivity (MFP) measurement (a term used interchangeably with total factor productivity (TFP) in this report) into the U.S. Federal statistical system. This measurement is different from the single factor productivity (also called partial productivity) measurement that attributes production to a single input factor, such as land in the case of crop yield. TFP is a measure that accounts for the contributions of all inputs in the calculation (such as land, capital assets, and labor), as well as intermediate inputs like energy, agricultural chemicals, materials, and purchased services. TFP growth measures the output changes that cannot be explained by changes in all inputs taken together.[1] TFP is also widely treated as an indicator of overall technical change under certain assumptions.

To improve the quality of U.S. agricultural productivity estimates, USDA has implemented two external reviews—one in 1978 by an American Agricultural Economics Association (AAEA) taskforce on Measuring Agricultural Productivity (USDA, 1980) and the other in 2014 by a panel of productivity experts from academia and Government (Shumway et al., 2016, 2017).[2] Some major recommendations from the AAEA taskforce review included:

(1) Index number procedures should move away from the Laspeyres index to the Divisia index, specifically for pesticides, fertilizers, and aggregate inputs.

(2) Input quality adjustments should be incorporated to ensure that inputs are measured in constant-quality units.

(3) The gross output approach for productivity measurement should be used rather than the value-added approach.

During the second review, conducted in 2014, the committee made a few methodological recommendations regarding the output and input measurement in the aggregate accounts and the reinstatement of the State-level accounts. The committee also suggested that USDA, ERS improve its data documentation and communication with data users and that USDA, ERS continuously explore new data sources to improve its input-quality measurement, such as investigating the American Community Survey (ACS) as an alternative or complementary data source for labor quality adjustment (Shumway et al., 2017).

Today, USDA, ERS bases its U.S. agricultural productivity statistics on a complex system of production and input accounts (USDA, ERS, 2023) that incorporate recommendations made by the AAEA task force

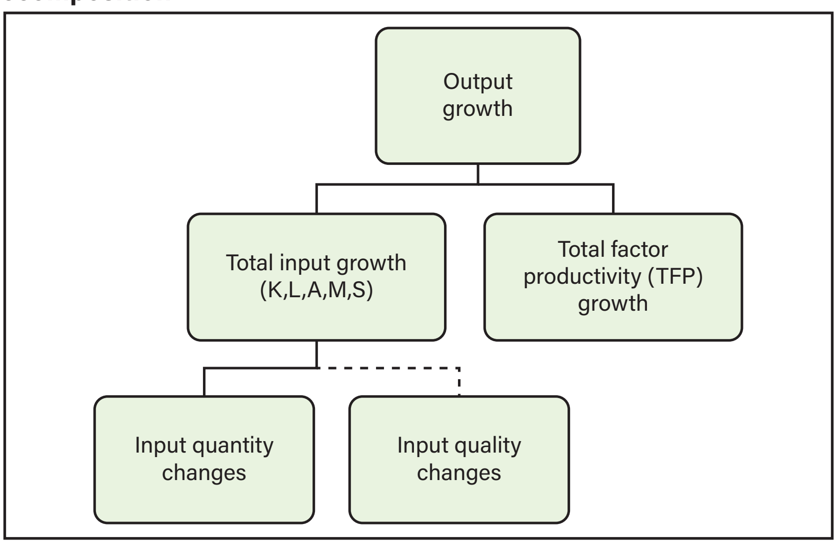
[1] TFP is often referred to as the Solow residual (Solow, 1957).

[2] While the second review was implemented in 2014, the report was published online in 2017.

(USDA, 1980) and major comments by a 2014 panel led by Shumway et al. (2017). The USDA, ERS model of agricultural productivity growth is based on a translog transformation frontier with multiple outputs and inputs. The model relates the revenue share-weighted growth of outputs to the cost share-weighted growth rates of labor, capital (including land), and intermediate inputs. One unique feature of the U.S. agricultural productivity data is that USDA, ERS economists account for input quality changes in measuring inputs wherever data are available. Therefore, USDA, ERS is able to provide a reasonable solution to the bias problem encountered in estimating unbiased measures of TFP presented in the U.S. agricultural productivity accounts.

The primary objective of this report is to describe in detail how USDA, ERS measures outputs, inputs, and total factor productivity in its U.S. agricultural productivity accounts. More significantly, the authors explain the methods employed in input quality measurement. Since input qualities are likely to vary over time, it is important to measure inputs in their constant qualities, especially for data spanning a long period of time. Figure 1 illustrates that both input quantity and quality play a role in determining total input growth, which in turn affects output growth and estimates of TFP. TFP can be overstated if input quality changes are not accounted for in the input measurement.

Figure 1
Output growth decomposition



Note: K indicates capital (excluding land); L indicates labor; A indicates land; M indicates materials such as energy, fertilizer, and pesticides; and S indicates purchased services such as repair and maintenance, custom machinery work, and purchased contract labor service. M and S are combinedly categorized as intermediate inputs in the U.S. agricultural productivity measurement. The dotted line indicates that if input quality is not accounted for in the input measurement, then its contribution to the output growth may be incorporated in the contribution of total factor productivity growth.

Source: USDA, Economic Research Service.

Calculating agricultural inputs, outputs, and total factor productivity requires data from many sources. The box "Major Data Sources for the U.S. Agricultural Productivity Accounts" provides detailed sources of data used in each step of measurement (outputs and inputs) in relation to each section of the report.

Major Data Sources for the U.S. Agricultural Productivity Accounts

Primary data were drawn from public sources and unpublished/confidential data sources. Value and quantity of production, marketing sales, and inventory changes were from the USDA, Economic Research Service (ERS) farm income balance sheets and USDA, National Agricultural Statistics Service (NASS) surveys. Prices for individual outputs (such as corn, soybeans, etc.) and inputs (tractors, farm structure, and machinery repair services) were from USDA, NASS, the U.S. Department of Commerce, Bureau of Economic Analysis (BEA), the U.S. Department of Labor, Bureau of Labor Statistics (BLS), and the U.S. Department of Energy, among others. Prices of individual fuel inputs (petroleum, natural gas, and electricity) were taken from the U.S. Department of Energy's Energy Information Administration Monthly Energy Review and from BLS.

For input quality adjustment, data from the following sources were used to measure quality-adjusted input prices and quantities:

- Agricultural fertilizer and pesticides: Data from GfK Kynetec AgroTrak database, Agricultural Information System (AgrAspire - Crop Protection and Seed), American Association of American Plant Control Officials, the Fertilizer Institute, and USDA, NASS were used to measure quality-adjusted hedonic prices for fertilizer and pesticides.
- Labor: Microdata came from the U.S. Department of Commerce, Bureau of the Census, American Community Survey (ACS), the Decennial Census of Population, the USDA's Agricultural Resource Management Survey (ARMS), and tabulated data from the Current Populations Survey (CPS) implemented by the Census Bureau and BLS, as well as public data from BEA, BLS, and USDA, NASS.
- Purchased contract labor services: We adopted microdata from the U.S. Department of Labor (DOL), Employment and Training Administration (ETA)'s National Agricultural Worker Survey (NAWS), and ARMS for the estimation.
- Land: We adopted data from the USDA's June Area Survey, Agricultural Economics and Land Ownership Survey, Census of Agriculture, and ARMS.

Measurement of Aggregate Output, Aggregate Input, and Total Factor Productivity

Theoretical Framework

Productivity growth is measured based on the growth-accounting theoretical framework (Solow, 1957). USDA, ERS defines the farm sector in the same way as in the U.S. Department of Commerce, Bureau of Economic Analysis' (BEA) National Income and Product Accounts (NIPAs).[3] This definition means that

[3] NIPAs are economic accounts that present the value and composition of national output and the types of incomes generated in the production of that output (U.S. Department of Commerce, Bureau of Economic Analysis (BEA), 2022).

minor goods and services (i.e., secondary outputs) for agriculture that are primary to other industries are included in the primary industry's output. There are a few exceptions, however, where the authors took the existence of certain (inseparable) secondary activities into account as a part of farm output. These exceptions were defined as activities whose costs cannot be separately observed from those of the primary agricultural activity (see United Nations (2009)). Examples include machine services for hire, custom feeding of livestock, farm forestry, and recreational activities that involve the means of production (hunting, fishing, and horse-back riding, for examples). Thus, the farm output came from two kinds of activities: agricultural activities such as livestock production or crop production and nonagricultural (or secondary) activities of farms.

The USDA, ERS construction of the farm sector production accounts is consistent with a gross output model of production. In contrast with the real-value-added method, farm output is defined in the USDA, ERS productivity accounts as gross production leaving the farm. Therefore, inputs are not limited to labor and capital but also include intermediate inputs. The goods produced and consumed within the farm that were not sold on the market are considered as self-cancelling transactions and do not enter either output or input accounts.

TFP growth is the difference between the total output growth and the total input growth. Hence, how we measured aggregate output and aggregate input would greatly affect TFP estimates. Since compositions of a specific category of outputs or inputs can change over time, it was not ideal to measure aggregate output or input by summing up all commodities or inputs by their physical quantities, such as adding tons of soybeans, corns, and apples together or adding counts of machinery and farm workers together. It was more desirable to use dollar values for aggregation and then deflate the values with proper price indices that have accounted for composition shifts among commodities within a specific category of products to reduce the aggregation error (Jorgenson & Griliches, 1967).

In the U.S. agricultural productivity accounts, we applied the Törnqvist index approach (a discrete approximation to a continuous Divisia index)[4] to calculate the price indices of aggregate output and aggregate input. The implicit quantities of aggregate output and aggregate input are in deflated dollar values (in constant dollars), using USDA, ERS-constructed price indices as the deflators.

Output

To measure the aggregate output, USDA, ERS economists started with disaggregated data on physical quantities and market prices of agricultural goods. The output quantity for each crop and livestock category consisted of quantities of commodities sold off the farm (including unredeemed Commodity Credit Corporation loans), additions to inventory, and quantities consumed in farm households during the calendar year. Off-farm sales in the aggregate accounts (U.S. national accounts[5]) are defined only in terms of output leaving the sector.[6]

[4] A Divisia index is a theoretical framework to develop an index number series for continuous time data on prices and quantities of goods. The index was first proposed and analyzed by François Divisia (Divisia, 1926). In practice, economic data are not measured in continuous time. Therefore, when a series is said to be a Divisia index, it usually means the series follows a procedure that makes a close analogue in discrete time periods, such as the Törnqvist index procedure (Diewert, 1993).

[5] The Commodity Credit Corporation (CCC) is a wholly-owned Government corporation. CCC was created in 1933 under a Delaware charter and reincorporated June 30, 1948, as a Federal corporation within the Department of Agriculture by the Commodity Credit Corporation Charter Act. CCC funds are used to implement specific programs established by Congress, as well as to carry out activities under the broad authorities of the CCC Charter Act. At this time, the principal programs established by Congress that are funded by CCC include: domestic farm income, price support and conservation programs under various statutes, including the Agricultural Act of 2014; foreign market development and other international activities of the Department of Agriculture under several statutes, including the Agricultural Trade Act of 1978; and activities of the United States Agency for International Development, under Title II of the Food For Peace Act.

[6] This definition on off-farm sales is different from what is measured in the State accounts. Off-farm sales in the State accounts also include sales to the farm sector in other States.

The corresponding price of a specific output reflects the value to the producer, as subsidies were added and indirect taxes were subtracted from market values. The measure of output also includes goods and services of nonagricultural (or secondary) activities when these activities could not be distinguished from the primary agricultural activity. Törnqvist indices of output were formed by aggregating the output of agricultural goods and the output of goods and services of inseparable secondary activities, using revenue-share weights based on shadow prices—the prices farmers receive or face for each commodity that reflect the market value, the U.S. Government subsidy, and/or the Government tax (or tax rebate) for that commodity.

In the U.S. productivity accounts, USDA, ERS economists group farm outputs into three types of goods: livestock and products (including meat animals, dairy, and poultry and eggs); crops (including food grains, feed crops, oil crops, vegetables and melons, fruits and nuts, and other crops); and farm-related output (including the output of goods and services from certain nonagricultural or secondary activities). At each stage of output construction, we constructed a price index for each output category first using the Törnqvist index number approach. Törnqvist price indices were calculated for consecutive periods, using average revenue shares from two periods as the weights.[7] Commodity revenue shares were calculated at different stages, using the value (price multiplied by production quantity) of each commodity or category of output divided by the total value of all outputs in the category or in the entire farm sector. Thus, the calculation did not refer to a single base year and could be chain-linked to any year assigning the number "1" or "100" to that specific year as the indexed year. We then constructed implicit quantities for each output category and the aggregate output, using constructed Törnqvist prices as the deflators.

Intermediate Inputs

Intermediate inputs included goods used in production during the calendar year, whether withdrawn from beginning inventories or purchased from outside the farm sector.[8] We classified intermediate inputs into six subcategories: feed and seed, energy, fertilizer and lime, pesticides, purchased services, and other intermediate inputs in the U.S. agricultural productivity accounts. Translog indices of intermediate inputs were constructed by weighting the growth rates of each subcategory of intermediate inputs named above by their value share in the overall value of intermediate inputs.

Open-market purchases of feed and seed inputs entered the farm sector as intermediate goods accounts.[9] Withdrawals from producers' inventories were also measured as outputs, intermediate inputs, and capital inputs. Beginning inventories of crops and livestock represent capital inputs and are discussed in the "Capital Inputs" section of this report. Additions to these inventories represented deliveries to final demand and were treated as part of output. Goods withdrawn from inventory were symmetrically defined as intermediate goods and recorded in the farm input accounts.

Data on current dollar consumption of petroleum fuels, natural gas, and electricity in agriculture were compiled for 1948–2021 at the national level. Prices of individual fuels were taken from the Energy Information Administration's Monthly Energy Review and USDA, NASS. The index of energy consumption was formed implicitly as the ratio of total expenditures (less State and Federal excise tax refunds) to the corresponding price index.

[7] Commodity revenue shares are calculated at different stages using the value (price multiplied by quantity) of each commodity, divided by the value of all outputs in a specific output category (wheat in the food grain subcategory, for example) or the value of an output subcategory in an output category (such as food grain subcategory in the crops category), or the value of an output category in the total value of the farm production (such as the crops category in total farm output).

[8] In the State accounts, the inputs also include those purchases from farms in other States.

[9] If one commodity was sold off-farm and was purchased by another farm to be used as an intermediate input in production, then that commodity would be counted as an output and an intermediate input in the U.S. agricultural productivity accounts.

Pesticides and fertilizers have undergone significant changes in quality over time, often improving. To measure input price and quantity in constant-efficiency units, we constructed price indices for fertilizers and pesticides using hedonic methods. Finally, price and implicit quantity indices were constructed for purchased services, such as contract labor services, machine services, and maintenance and repairs. Since available data were limited to nominal expenditures for various services, we employed price indices from various sources (such as BLS, BEA, and USDA, National Agricultural Statistics Service (NASS)) as deflators. To account for quality changes embodied in contracted labor, we estimated a hedonic wage function. Purchased machine services substituted for own-capital input. Therefore, we constructed the implicit quantity of purchased machine services as the ratio of expenditures to an index of rental prices of agricultural machinery (i.e., farm tractors or agricultural machinery excluding tractors).

Labor Input

The labor accounts for the aggregate farm sector incorporate the demographic cross-classification information of the agricultural labor force. Required data came from both establishment and household surveys using the RAS[10] procedure. The resulting estimates of employment, hours worked, and labor compensation were controlled to the total numbers for the farm sector. The numbers were based on establishment surveys that underlie the NIPA and special tabulation work by BLS, derived from the Current Population Survey (CPS) (see the "Labor Input" section for a more detailed description of how we adjusted for quality changes in the labor input measurement).

The final indices of labor input for the aggregate farm sector were constructed using the Törnqvist index number approach based on the demographically cross-classified hours and compensation data. Labor hours having higher marginal productivity (wages) were given higher weights in forming the index of labor input than were hours having lower marginal productivities. As a result, labor prices were quality-adjusted to account for demographic compositional shifts over time. Also, labor input was measured as in its constant efficiency unit—an implicit quantity of labor compensation deflated by quality-adjusted labor price (Wang et al., 2022; Jorgenson & Griliches, 1967).

Capital Input

In the U.S. productivity accounts, the construction of capital series begins with estimating the capital stock and rental price for each asset type. For depreciable assets, the perpetual inventory method was used to develop stocks from data on investment (United Nations, 2009). Depreciable assets include automobiles, tractors, trucks, farm structures, and other farm machinery. For land and inventories, capital stocks were measured as implicit quantities derived from balance sheet data in the aggregate account. Implicit rental prices for each asset were based on the correspondence between the purchase price of the asset and the discounted value of future service flows derived from that asset.

Depreciable Assets

Under the perpetual inventory method (PIM), capital stock K at the end of each period t was measured as the sum of all past investments I in constant dollars, each weighted by its relative efficiency, d_τ:

$$K_t = \sum_{\tau=0}^{\infty} d_\tau I_{t-\tau} \qquad (1)$$

where d_τ is approximated by a hyperbolic efficiency function:

[10] RAS is a biproportional balancing method that allows for adjusting rows and columns back and forth through an iterative process (Trinh & Phong, 2013).

$$d_\tau = (L-\tau)/(L-\beta_\tau), 0 \le \tau \le L \qquad (2)$$

$$d_\tau = 0, \tau \ge L$$

L is the service life of the asset, τ represents the asset's age, and β is a curvature or decay parameter. The value of β was restricted only to values less than or equal to 1. For values of β greater than zero, the efficiency of the asset approaches zero at an increasing rate. For values less than zero, efficiency approaches zero at a decreasing rate.

There was little empirical evidence regarding a precise value for β. We followed the results from two studies by Penson et al. (1977) and Romain et al. (1987). The studies showed that efficiency decay occurs more rapidly in the later years of service, corresponding to a value of β in the 0 to 1 interval. In the USDA, ERS practice, we assumed that the efficiency of a structure declined slowly over most of the structure's service life until a point is reached where the cost of repairs exceeds the increased service flows derived from the repairs, at which point the structure was allowed to depreciate rapidly (β=0.75). The decay parameter for durable equipment (β= 0.5) assumes that the decline in efficiency was more uniformly distributed over the asset's service life (Ball et al., 2008; Ball et al., 2016).

We considered an efficiency function that holds β constant and allows L to vary. Investment is a bundle of different types of capital goods. Each type of the capital goods was a homogeneous group of assets in which the actual service life, L, was a random variable reflecting quality differences, maintenance schedules, etc. For each asset type, there existed some mean service life, $\bar{L}$, with some distribution of actual service lives around it. To measure the amount of capital available for production, we needed to first determine the actual service lives for each type of capital asset. We also assumed that the underlying distribution is the normal distribution truncated at points two standard deviations above and below the mean service life. Mean service lives corresponded to 85 percent of the U.S. Department of the Treasury's "Bulletin F" (U.S. Department of Treasury, 1960).[11]

Capital Rental Prices

We assumed that farms would add to their capital stock so long as the present value of the net revenue generated by an additional unit of capital exceeds the purchase price of the asset. This formula can be stated algebraically as:

$$\sum_{t=1}^{\infty}\left(p\frac{\partial y}{\partial K} - w_K\frac{\partial R_t}{\partial K}\right)(1+r)^{-t} > w_K \qquad (3)$$

Where p is the price of output (y), $\partial y/\partial K$ is the marginal product of capital K so the gross revenue in each period will rise by $p(\partial y/\partial K)$ with an additional unit of K; w_K is the price of investment assets; $\partial R_t/\partial K$ is the increase in replacement (R) in period t required to maintain the capital stock at the new level, so net revenue will rise by only $p(\partial y/\partial K) - w_K(\partial R_t/\partial K)$; and r is the real discount rate. To maximize net present value, farms will continue to add to capital stock until this equation holds as an equality[12] (see Ball et al. (2016), for more details):

$$p\frac{\partial y}{\partial K} = rw_K + r\sum_{t=1}^{\infty} w_K\frac{\partial R_t}{\partial K}(1+r)^{-t} \equiv c \qquad (4)$$

where c is defined as the implicit rental price of capital. The term, rw_K represents the opportunity cost associated with the initial investment.

The term $r\sum_{t=1}^{\infty} w_K\frac{\partial R_t}{\partial K}(1+r)^{-t}$ is the present value of the cost of all future replacements required to maintain the productive capacity of the capital stock.

[11] USDA, ERS economists will investigate the service lives information cited by BLS, BEA, or other statistical agencies and modify their estimates in the future if needed.

[12] The required condition is marginal revenue equals marginal cost when farm operators try to maximize their profits.

Let F denote the present value of the stream of capacity depreciation on one unit of capital according to the mortality distribution m:

$$F = \sum_{\tau=1}^{\infty} m_\tau (1+r)^{-\tau} \qquad (5)$$

Replacement at time *t* is equal to capacity depreciation at time t:

$$\sum_{t=1}^{\infty} \frac{\partial R_t}{\partial K}(1+r)^{-t} = \sum_{t=1}^{\infty} F^t = \frac{F}{(1-F)} \qquad (6)$$

so that:

$$c = \frac{r w_K}{(1-F)} \qquad (7)$$

The real rate of return *r* in the above expression, was calculated as the nominal yield on investment-grade corporate bonds less the rate of inflation as measured by the asset-specific prices. An ex-ante rate was obtained by expressing observed real rates as the Autoregressive Integrated Moving Average (ARIMA) process (a method for forecasting or predicting future outcomes based on a historical time series). We calculated *F* holding the required real rate of return constant for that vintage of capital goods. In this way, implicit rental prices, *c*, were calculated for each asset type (except for inventory, where the rate of inflation was measured by the implicit deflator for gross domestic product for data consistency). Asset prices and investment data were drawn from BLS, USDA, ERS, and USDA, NASS. For the special case where $d_\tau = \delta(1-\delta)^{\tau-1}$ (assumed by Jorgenson, 1963), $F=\delta/(r+\delta)$, and $c=w_k(r+\delta)$.

Finally, Törnqvist quantity indices of capital input (service flow) for the aggregate farm sector were constructed by aggregating the growth rates of different capital assets, using cost-share weights based on the asset-specific rental prices.

Inventory

Beginning inventories of crops and livestock were treated as capital inputs. The number of animals on farms was available from annual surveys, as were the stocks of grains and oilseeds. We applied December average prices from the previous year in order to value commodities held in inventory in the current year. The implicit rental price of inventory was calculated using the expected real rate of return (ex-ante real rate), assuming zero decay.

Land Input

The definition of land in farms in the USDA, Census of Agriculture includes all grazing land (including reservation grazing land, land in grazing associations, and land leased for grazing) except public lands leased for grazing on a per-head basis.[13] From land in farms, we excluded the land area in roads and house lots and miscellaneous areas such as marshes, open swamps, and bare-rock areas.[14]

The USDA Census of Agriculture reports data on the value of farm real estate (i.e., land and structures); the census does not provide data on land values separately. Historically, the value of farm real estate was partitioned into its components using information from the USDA's Agricultural Economics and Land Ownership Survey (AELOS). However, AELOS was last conducted in 1999. Starting with the updates of the 2013 accounts, we relied on the annual USDA Agricultural Resource Management Survey (ARMS) to derive estimates of the value of land from data on the value of farm real estate (Ball et al., 2016).

[13] Service flows from public lands were estimated from grazing fees paid (Bureau of Land Management and USDA, Forest Service) and included in intermediate input.

[14] Land enrolled in the Conservation Reserve Program (CRP) was a component of capital stock, while conservation service flows were considered a component of output.

To estimate the stock of land, we constructed price and implicit quantity indices of land in farms. We compiled data on acres of land in farms and the average value (excluding buildings) per acre for each county in each State, using information from the Census of Agriculture. Intermediate years were interpolated. Land enrolled in the USDA's Conservation Reserve Program (CRP) was a component of capital stock, while conservation service flows were considered a component of output included in the "other farm-related output" category.

The cost of land service flows was derived using the accounting identity with the value of the total product equal to the total factor outlay.

Total Factor Productivity

Total factor productivity is a measure that accounts for "all"[15] inputs taken together in the farm production process and is usually defined as the ratio of total output over total input—output per unit of total input. The USDA model of productivity growth is based on a translog transformation frontier. The model relates the growth rates of multiple outputs to the cost-share-weighted growth rates of labor, capital, and intermediate inputs. TFP growth is the difference between the growth of aggregate output and the growth of all inputs taken together. We measured TFP growth using the Törnqvist index number approach. TFP growth over two time periods was defined as:

$$ln\left(\frac{TFP_t}{TFP_{t-1}}\right) = \sum\left(\frac{R_{it}+R_{it-1}}{2}\right) ln\left(\frac{Y_{it}}{Y_{it-1}}\right) - \sum\left(\frac{W_{jt}+W_{jt-1}}{2}\right) ln\left(\frac{X_{jt}}{X_{jt-1}}\right) \quad (8)$$

where R_i are output revenue shares, Y_i are individual outputs, W_j are input cost shares, X_j are individual inputs, and t and t–1 are time subscripts, i denotes the i^{th} output, and j denotes j^{th} input.

In practice, we employed detailed prices and quantities for individual commodities to estimate prices and implicit quantities for total output and its three categories—livestock and products, crops, and farm-related output—and 10 subcategories: meat animals, dairy, poultry and eggs, food grains, feed crops, oil crops, vegetables and melons, fruits and nuts, other crops, and other farm-related output. We also employed various data sources to measure prices and implicit quantities for total input and its 3 categories—capital, labor, and intermediate inputs—as well as 12 subcategories: durable equipment, service buildings, land, inventories, hired labor, self-employed and unpaid family, feed and seed, energy, fertilizer and lime, pesticides, purchased services, and other intermediate input.

[15] While researchers consider "all" inputs used on farms in their measurement, there may exist data limitation when some inputs are not easily observed or measured, such as soil characteristics or rainfall.

Input-Quality Measurement in the U.S. Agricultural Productivity Accounts

Given that some inputs (such as fertilizer, pesticides, and labor) have undergone significant changes in their quality over time, we needed to consider those changes and measure inputs in their constant-efficient units in productivity analysis. As Jorgenson and Griliches (1967) indicated, "quality changes" problems can be a major potential explanation of productivity growth and need to be accounted for as a part of the source of growth in productivity measurements.

Quality-adjustment methods use the information on input characteristics and link price variations to changes in attributes embodied in an input unit. While there are many methods of adjusting for quality changes in price index construction (United Nations System of National Accounts (UN-SNA), 2009), we only addressed the approaches employed in the U.S. agricultural productivity accounts.

Theoretical Framework: Hedonic Approach Versus Index Number Approach

In productivity analysis, economists employ various price indices to deflate output and input values to get the real values of those aggregates. Nevertheless, other factors, such as input quality differences, may drive price variation. An input item may undergo price changes over time or price variations due to differences in characteristics. The United Nations System of National Accounts (UN-SNA) pointed out that price index estimates that fail to fully incorporate the increase in quality over time would "overstate price changes and understate volume changes" (United Nations, 2009).

UN-SNA introduced the term "volume index" as "an average of the proportionate changes in the quantities of a specified set of goods or services between two periods of time." UN-SNA emphasized that "the quantities compared over time must be those for homogeneous items and the resulting quantity changes for different goods and services must be weighted by … their relative values in one or other, or both, periods" (United Nations, 2009). Under such concepts, the term "quantities" needs to be adjusted to reflect changes in quality. Following United Nations (2009) and Jorgenson et al. (2005), we use the terms "volume" and "constant-quality quantity index" as synonymous in the rest of the paper.

Hedonic Method

In general, a hedonic price function expresses the price of a good or service as a function of the quantities of the characteristics the function embodies. Thus, the hedonic price function may be expressed as $W_p = W(\boldsymbol{X}, \boldsymbol{D})$, where W_p represents the price of the commodity/input of interest, $\boldsymbol{X}$ is a vector of characteristics or quality variables, and $\boldsymbol{D}$ is a vector of other variables.

The hedonic method was pioneered by Waugh (1928) in a vegetable price study with quality factors, while the term hedonic was first introduced by Court (1939) in an automobile study. The term and method were later adopted and popularized by Griliches (1961, 1971) and applied by many others, including: Rosen (1974), Triplet (1987, 2004), Fernandez-Cornejo and Jans (1995), and Kellog et al. (2002), among others.

The selection of other variables (denoted by $\boldsymbol{D}$) depends not only on the underlying theory but also on the objectives of the study. If the main objective of the study is to obtain price indices adjusted for quality, the only variables that should be included in $\boldsymbol{D}$ are time or regional dummy variables (depending on purposes), which will capture all price effects other than quality. After allowing for differences in the levels of the characteristics, the part of the price difference not accounted for by the included characteristics will be reflected in the coefficients on the dummy variables.

Economic theory places few, if any, restrictions on the functional form of the hedonic price function. To allow for a normal distribution in the dataset employed in our analysis, we adopted a Box-Cox transformation method (see Box and Cox (1964) and Sakia (1992) for more discussion). The generalized linear form presented below conveys how the dependent variable and each of the continuous independent variables was represented by the Box-Cox transformation. This transformation is a mathematical expression that assumes a different functional form depending on the transformation parameter, λ. The transformation can assume both linear and logarithmic forms, as well as intermediate nonlinear functional forms. We chose the value of λ that provided the best approximation for the normal distribution of the targeted variable. The general functional form of the model is given by:

$$W_p(\lambda_0) = \sum_n \alpha_n X_n(\lambda_n) + \sum_d \gamma_d D_d + \varepsilon \qquad (9)$$

Where $W_p(\lambda_0)$ is the Box-Cox transformation[16] of the dependent price variable, $W_p>0$; that is:

$$W_p(\lambda_0) = \begin{cases} \frac{W_p^{\lambda_0}-1}{\lambda_0}, \lambda_0 \neq 0 \\ \ln W_p, \lambda_0 = 0 \end{cases} \qquad (10)$$

Similarly, $X_n(\lambda_n)$ is the Box-Cox transformation of the continuous quality variable X_n where $X_n(\lambda_n) = \left(X_n^{\lambda_n} - 1\right)/\lambda_n$ if $\lambda_n \neq 0$ and $X_n(\lambda_n) = ln\, X_n$ if $\lambda_n = 0$. Variables represented by D are time dummy variables, not subject to transformation; α_n and γ_d are unknown parameter vectors, and ε is a stochastic disturbance term.

While the functional form can be selected based on the λ estimate, the form can sometimes rely on the economist's judgment as well, given personal knowledge of the data, commodity, and experiences.

Selection of Dummy Variables, Characteristics, and Structural Changes

The selection of dummy variables depended on the purpose of the price index we were constructing. If the purpose of the analysis was to construct a time series of annual price indices, then *D* could be yearly dummy variables. If the purpose was to construct relative prices across political boundaries, then *D* could be region dummy variables, such as State or country dummies. *D* could also be a combination of both time and region dummy variables when needed.

To construct constant-quality price indices for inputs, it was necessary to consider characteristics that may affect the productive efficiency and marginal value of the input using all the data available. With a single regression model estimated, we assumed that each characteristic's marginal value was constant over time. However, this assumption may not be true over a long period. There are a few ways to deal with this issue. One is to construct structure tests over a long time series of data and then run the hedonic regression models separately, using a portion of the dataset when structural breaks are detected. Another approach is to assume marginal values of the characteristics change every year and pool the data together in 2 successive years to conduct hedonic regression estimates.

[16] The Box-Cox transformation has its limitation and may place some restrictions on the error term in the hedonic model (Santos-Silva & Tenreyro, 2006). Machine-learning algorithms are an alternative predictive tool to the Box-Cox transformation. See Mullainathan and Spiess (2017) for information on machine-learning techniques applied in econometrics.

Index Number Approach

"Quality change" is sometimes referred to as a special type of aggregation error (Jorgenson & Griliches, 1967). As examples, aggregating investment assets of different vintages by adding together their quantities, getting intermediate input "quantity" estimates by summing up the dollar values of all intermediate input items and deflating total values with one single deflator, or adding up all the land acreages to get the estimate of land stock could all result in such errors. Jorgenson and Griliches indicated that "quality changes" due to aggregation errors arise when items with different qualities, productive efficiencies, and growth rates are aggregated rather than treated as different items in the calculation, causing a bias. They proposed a way to eliminate this type of bias by constructing a Divisia index for each input group by using individual items within that group. Therefore, selecting a proper classification method to separate input items within each input category is crucial for adjusting for this kind of "quality change" or "compositional shift."

In USDA, ERS U.S. productivity accounts, we employed the Törnqvist index number approach (a Divisia index that considers the use of changing weights in each period of the analysis) to construct quality-adjusted input prices and quantities (volumes). This method requires using much more detailed and disaggregated data. A price index for a specific type of input can be expressed as a composite index based on the level of each group of characteristic combinations and prices from each unique unit of that type of input.

A quality-adjusted quantity index of a specific type of input based on the Törnqvist index number approach can be expressed as:

$$ln\left(\frac{X_t}{X_{t-1}}\right) = \sum \frac{1}{2}(v_{mt} + v_{mt-1}) ln\left(\frac{X_{mt}}{X_{mt-1}}\right) \qquad (11)$$

Where X denotes the volume of input X to be measured, such as labor or land; $ln\left(\frac{X_t}{X_{t-1}}\right)$ represents the growth rate of quality-adjusted input X; v_m is the cost share for characteristics group m, X_m is the level (quantity) of the specific characteristics group m; and t and $t\text{-}1$ are time subscripts.

If our purpose was to construct a quality-adjusted price index first, then we could replace all the quantity notations X in equation (4) with price notations P_x. A quality-adjusted quantity estimate could then be retrieved using the total values deflated by the quality-adjusted price index.

USDA, ERS has adopted both the hedonic method and the index number approach over the years to adjust input quality changes wherever data are available. The following sections provide some examples of calculating the quality-adjusted prices/quantities in the U.S. agricultural productivity accounts using either the hedonic or index number approach.

Agricultural Chemicals

Fertilizers and pesticides have undergone significant changes in input quality over the study period. Since the input price and quantity series used in a study of productivity need to be denominated in constant-efficiency units, we constructed price indices for fertilizers and pesticides using hedonic methods.

Fertilizer

The nutrient components contained in each multigrade fertilizer material vary across products and over time. Given the heterogeneity of the fertilizer materials, it is not appropriate to compute total fertilizer use by simply adding the quantities of all fertilizers applied. Griliches (1958, 1991) ran the first "hedonic" regression model in measuring fertilizer prices, relating prices of different mixes of fertilizers to their formulation of nitrogen (N), phosphorus (P), and potash (K). While Griliches did not actually use the term "hedonic" in his 1958 paper, he did postulate an alternative for constructing a constant-quality price index for fertilizer. Today, USDA, ERS adopts a similar hedonic regression technique to estimate quality-adjusted prices and quantities for fertilizer materials in the U.S. agricultural productivity accounts.

A compound fertilizer was assumed to comprise only three important nutrients: nitrogen, phosphorus, and potash. Their characteristics were measured as the percentage concentration of the nutrient within the fertilizer; the nature of the nutrients has not changed through time, but a variety of more concentrated products have become available. These nutrients perform different functions. We were interested in their implicit prices to aggregate those nutrients into a fertilizer index. Regression analysis was employed to estimate the implicit prices of N, P, and K and in relevant fertilizers, and the results reported are an average of simple (only N, P, or K) and compound fertilizers (weighted by quantities of nutrients applied in each form).

To obtain a price index of fertilizer, we regressed the prices of single nutrient and multigrade fertilizer materials on the proportion of nutrients contained in the materials. The regression model can be expressed as:

$$P_{it} = \sum_{t=1}^{T} \delta_t D_t + \sum_{j=1}^{J} \beta_j x_{ijt} + \varepsilon_{it} \qquad i = 1, \ldots, N. \qquad (12)$$

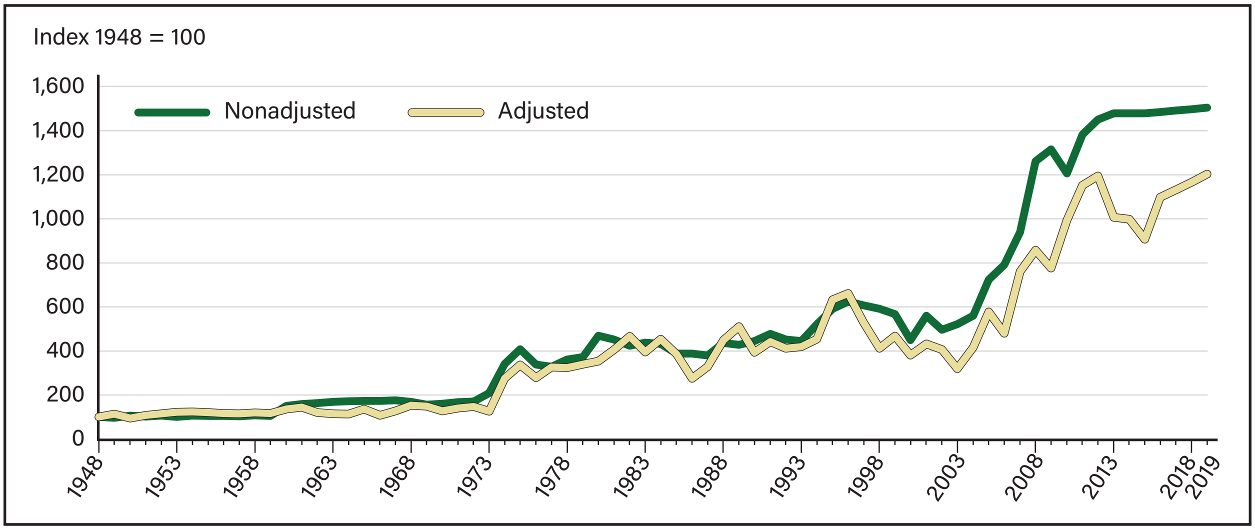
Where $P_{i,t}$ denotes the price of a specific grade of fertilizer i in year t; x_{ij} denotes a j^{th} characteristic (N, P, or K) of the ith grade of fertilizer; D_t is a time-dummy variable (yearly) taking a value of 1 for year t and 0 otherwise; δ_t and β_j are parameters to be estimated; and ε_{it} is a stochastic disturbance term. The empirical fertilizer hedonic regression is best fit with a linear form based on our data and estimates. When the above model is linear, β_j can be interpreted as the shadow price (implicit value) of the j^{th} characteristic. The variable δ_t is a constant-quality price index.

Overall, crop production uses close to 50 different fertilizer products, which have different compositions of N, P, and K.[17] The regression model specified in equation (12) was conducted using 14 single fertilizers and multiproduct combinations identified in the Commercial Fertilizers Incorporated report mentioned in the Data sources below. We also use the proportion of a given type of fertilizer to the total fertilizer expenditure as the weight. The robustness of the above equation was tested by examining the constancy of the estimated parameters employing a sequence of Chow tests (Chow, 1960).[18] The observations were successfully pooled into longer periods until the hypothesis of no structural change was rejected. The result of these estimations is the hedonic price for fertilizer (see figure 2 for comparison). The corresponding quantity indices are formed implicitly as the ratio of total expenditures to its price index (see figure 3 for comparison).

[17] These compositions include anhydrous ammonia, urea, etc., as elaborated upon in farmdoc, University of Illinois, and Ag Decision Maker, Iowa State University.

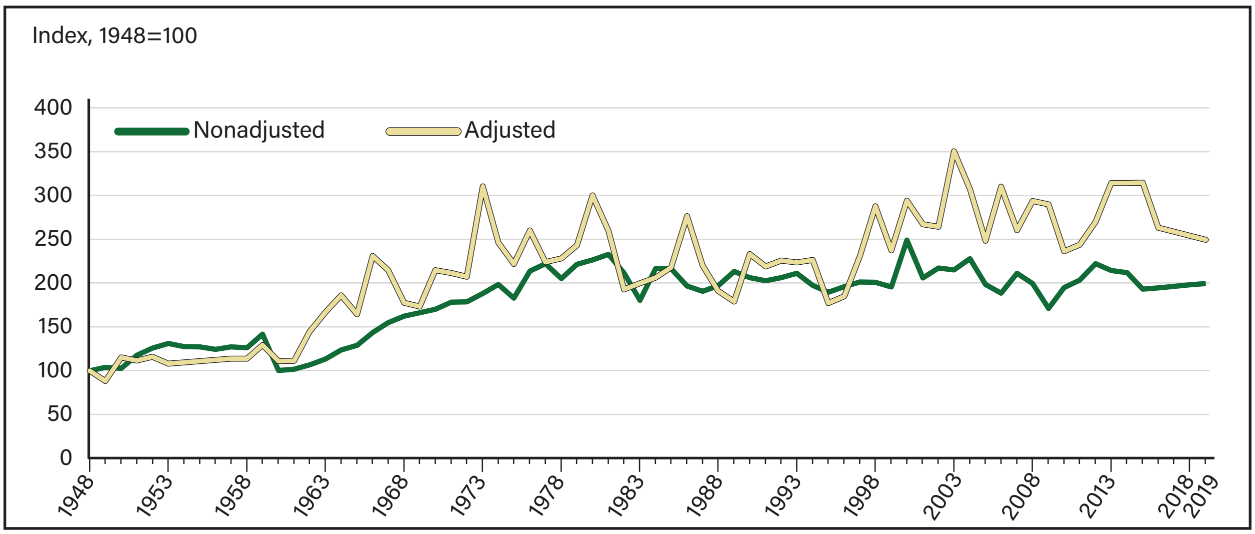
[18] The Chow test is a test of whether the true coefficients in two linear regressions on different data sets are equal.

Figure 2
Quality-adjusted and nonadjusted fertilizer prices in the United States, 1948–2019



Source: USDA, Economic Research Service.

Figure 3
Quality-adjusted and nonadjusted fertilizer quantities in the United States, 1948-2019



Source: USDA, Economic Research Service.

Data sources for fertilizer

The information required to generate quality-adjusted fertilizer price characteristics was obtained from the following sources:

(1) The main fertilizer quantity data were from the Association of American Plant Food Control Officials and Commercial Fertilizers Incorporated.

(2) Prices paid by farmers were from *Agricultural Statistics* and from farmdoc website (University of Illinois) and Ag Decision Maker (Iowa State University).

Pesticides

Over time, U.S. farmers have relied on pesticides to minimize loss and damage due to pests. Chemical pesticides (which include herbicides, insecticides, and fungicides) are typically applied on the fields by spraying.[19] Recent advancements have seen the emergence and widespread use of genetically engineered crops that are insect resistant and herbicide tolerant, contributing to a substantial shift in the application of pesticides. Further, over time, the active ingredients in pesticides have continued to evolve, altering the potency, persistence, toxicity, absorption rate, application rate, and—most importantly—the prices of pesticides (Nehring, 2019). Since 2000, approximately 30 new ingredients have been introduced. Currently, the largest proportion of active ingredients include glyphosate and atrazine. Active ingredients also include acephate, acetochlor, clothianidin, mancozeb, mesotrione, metolachlor, paraquat, and copper, among others.

There are some potential factors that affect producers' decisions in selecting pesticides, including:

- Widespread adoption of genetically engineered crops has led to reductions in insecticide use and changes in the type of pesticides used (Fernandez-Cornejo & Caswell, 2006).
- Changes in the mix of crops: There has been a substantial shift in acreage towards corn and soybeans. This shift has impacted the quantity and mix of pesticides, with these two crops now accounting for the majority of pesticide use. The eradication of the boll weevil has helped reduce pesticide use in cotton-growing areas (Perry et al., 2016).
- Weed resistance to newer herbicides has led to expanded use of some older herbicides.
- Relative price changes: The price of glyphosate and nonglyphosate material per unit of active ingredients has influenced use. Pesticide prices rose 87 percent and wages rose by 200 percent between 1980 and 2016. These changes in relative prices have encouraged farmers to adopt practices that reduce the use of other inputs and increase the use of pesticides.
- Environmental awareness about factors such as persistence and toxicity of pesticide use has begun to resonate among communities impacted by agricultural pesticide practices, resulting in a reduction of pesticide use in some areas.

Therefore, when conducting the measurement of quality-adjusted pesticide prices, we also needed to consider the variety of crops planted in different areas. To capture the changes in characteristics embodied in the pesticides, we adopted a hedonic approach to the measurement. The implicit quantities of pesticides were retrieved by using pesticide expenses deflated by quality-adjusted pesticides prices.

Hedonics and Quality-adjusted Pesticides

Pounds of pesticides applied is an unsatisfactory measure of pesticide quantity as it treats all active ingredients equally. Any unadjusted estimates, including TFP indices, would be biased as the estimates would comprise incorrect measures. A quality-adjusted measure of pesticide can be represented using the following hedonic expression (Fernandez-Cornejo & Jans, 1995):

$$P_{it}(\lambda_1) = \sum_{t=1}^{T} \gamma_t D_t + \sum_{m=1}^{M} \beta_m x_{mit}(\lambda_2) + \varepsilon_{it} \quad (13)$$

Where $P_{it}(\lambda_1)$ is the Box-Cox transformation of the price of a specific active ingredient, *i*, such as atrazine, glyphosate, or metolachlor. The first variable on the right-hand side, D_t is the year dummy, Υ_t are the parame-

[19] Use of pesticides for organic production is highly regulated. Organic crop producers are prohibited from using synthetic pesticides; thus, the producers typically rely on nonsynthetic chemicals, such as—sulfur, spinosad, potash soap, and pyrethrin. Alternatively, production practices such as crop rotation, tillage, and adjustments of planting and harvesting dates are used to minimize yield losses due to pests.

ters to be estimated, and $x_{mit}(\lambda_2)$ is the Box-Cox transformation of the m^{th} quality attributes embodied in a specific active ingredient i. Major attributes comprise:

(1) The application rate—a measure of the chemical's potency.

(2) The chronic toxicity score, which captures the hazardous characteristics. The score is measured as the inverse of the water quality threshold and serves as an indicator of environmental risk. Thus, the lower the index, the lower is the potential environmental risk of the chemical.

(3) Persistence—which defines the share of pesticides with a half-life of less than 60 days, so that the lower the indicator, the less persistent the pesticide.

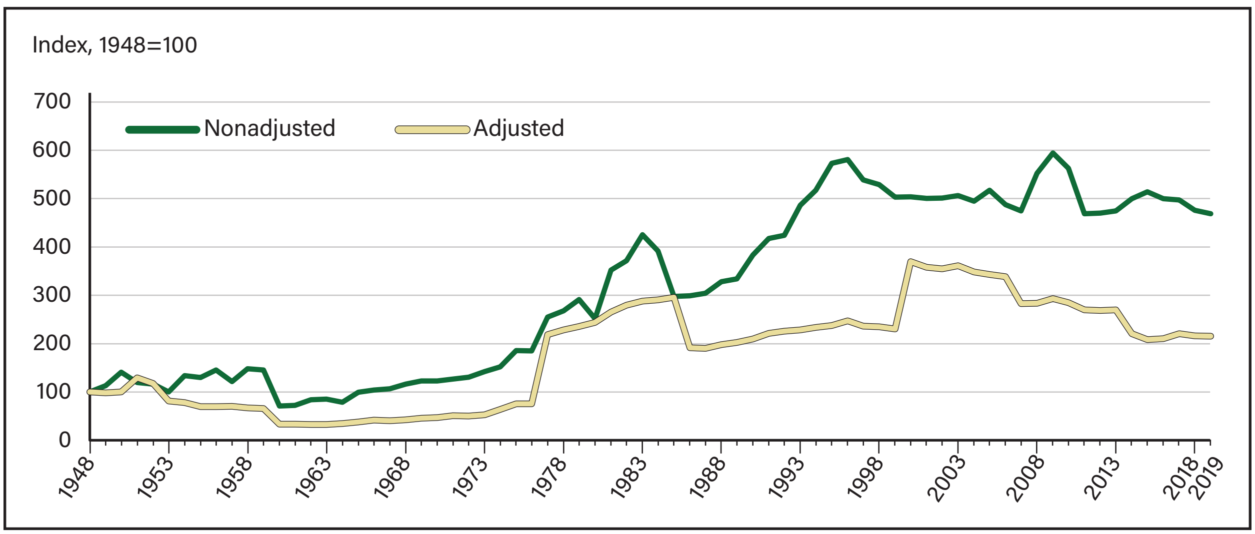
(4) The absorption rate—a coefficient that measures the degree to which the pesticide binds to soil particles.

(5) Water solubility—which captures the leaching potential, that is, the amount of pesticide in milligrams that would dissolve in 1 liter of water; and vapor pressure—which measures how readily a chemical evaporates into the ambient atmosphere.

The second variable, D_t, is a time-varying fixed-effect variable that captures price effects unrelated to quality changes, and ε_t is an independent random variable with distribution $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. Finally, $\beta_m \forall m = 1, ., M$, and γ_t are parameters to be estimated, and $\lambda_i \forall i = 1, 2$—captures the Box-Cox transformation used to manage nonlinearity of the model, and the subscripts i and t represent state and time, respectively. The result of these estimations is the hedonic price for pesticides (see figure 4 for comparison). The corresponding quantity indices are formed implicitly as the ratio of total expenditures to its price index (see figure 5 for comparison).

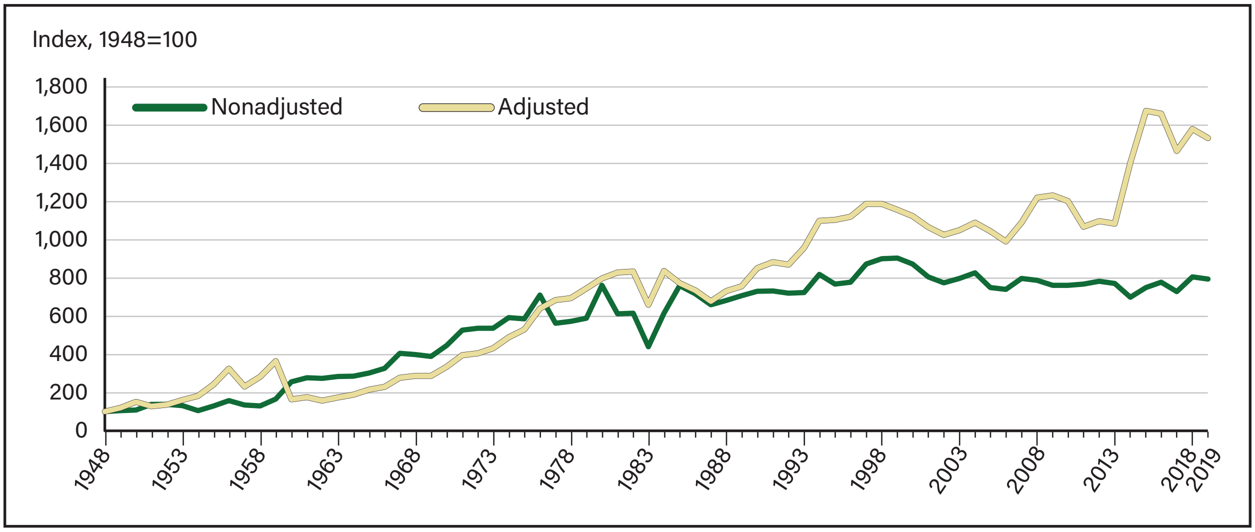
Figure 4

Quality-adjusted and nonadjusted pesticide prices, 1948–2019



Source: USDA, Economic Research Service.

Figure 5
Quality-adjusted and nonadjusted pesticide quantities, 1948–2019



Source: USDA, Economic Research Service.

Data Sources for Pesticides

Information required to generate price characteristics was obtained from the following sources:

(1) USDA, NASS: Information included application rates and pounds applied by active ingredients between 1948–1986, crop-specific application rates, and pounds applied by active ingredients by State for corn between 1990–2018 and cotton between 1990–2019.

(2) S&P Global: This data covered the U.S. use of pesticides by crop and brand.

(3) DOANE (Doane Pesticide Profile Study - 1987–2008): Proprietary data made available to USDA, ERS. The information included application rates and pounds by active ingredients, alongside implicit prices.

(4) Kynetec (AgroTrack table, U.S. Geological Survey website (1992–2020)): This information was available to USDA, ERS under a collaborative agreement with the U.S. Environmental Protection Agency (EPA). The information provided includes application rates and pounds applied, as well as implicit prices at the county level.

(5) Agrispire: Proprietary data that were purchased by USDA, ERS on agricultural chemical usage between 2012 and 2019. The information comprised implicit prices paid and application rates and pounds paid by active ingredient by crop.

(6) ChemInfo (USDA, Natural Resources Conservation Service (NRCS)/EPA sources): The data comprised information on environmental and toxicity attributes.

Purchased Contracted Labor Services

Farm operators sometimes purchase contracted labor services from contract providers for certain tasks on farms, especially in fruit and vegetable production. The workers are not employed by farm operators and hence are not counted as hired labor. Farm survey respondents were able to report expenses but not employment or hours for such workers. The purchased contracted labor services are reported in the U.S. agricultural productivity accounts as part of purchased services in the intermediate inputs category. Because there were no available data on hours worked, USDA, ERS estimated implicit quantities of purchased contracted labor services by dividing expenditures with a price index. Until 2000, USDA, ERS used "piece rate"[20] information from USDA, NASS to deflate these expenditures, but this information is no longer available. USDA, ERS has replaced this information with a new deflator based on a hedonic method (see Wang and Lucado (2024) for more details).

Contracted labor is viewed as a bundle of characteristics that contribute to the productivity derived from its use. The imputed prices of demographic characteristics are the marginal prices that are valid at the sample means, compared with actual average wages. For this purpose, we employed a different data source, the U.S. Department of Labor Employment and Training Administration (ETA)'s National Agricultural Workers Survey (NAWS), which has contracted worker information and other more detailed demographic characteristics data that are not available in the U.S. Census of Population and American Community Survey (ACS). Specifically, educational level is not reported in a categorized format as in the ACS, but it is by years of schooling in NAWS.[21] A hedonic function (in terms of years of farmwork experience, gender, educational attainment measured as schooling years, language skill, and legal status) was estimated with controlled variables. These variables include employment types and tasks in fruit and nuts, horticulture, vegetables, or others, as well as geographic and time variables. An econometric problem associated with the hedonic wage equation is that the probability of a worker being hired by a contract provider or directly by a farm operator may also be correlated with an error term in the wage equation. To correct for possible sample selection bias, we employed a hazard technique suggested by Heckman (1979).

Consider a hedonic wage function with a general form:

$$w_i = \sum_{m=1}^{M} \beta_m x_{mi} + \sum_{n=1}^{N} \gamma_n z_{ni} + \delta D_i + \varepsilon_i \qquad (14)$$

Where w_i represents a hedonic price of the purchased contracted labor service input; x_m are quantities of the characteristics embodied in the labor service—including experience, age, gender, education attainment, and language skill; z_n are features that may affect the level of wage rate, such as legal status and work type; and D_i is a binary variable representing the worker's employment type selection—employed by a farm operator (hired labor) or employed by a contractor (contracted labor), β, γ, δ are parameters to be estimated. We also add time and region dummies to control for the time- and geography-variant factors when we conduct the analysis.

Employee type selection is one of the explanatory variables in equation (14). However, the decision about the employee type also may be endogenous and can be explained by other independent variables shown in the expression below:

$$D_i^* = \acute{\boldsymbol{\tau}} \boldsymbol{Z}_i + u_i \qquad (15)$$

where $\boldsymbol{\tau}$ is a vector of parameters to be estimated, $\boldsymbol{Z_i}$ is a vector of independent variables. D_i=1 if $D_j^* > 0$, 0 otherwise.

If some of the independent variables are the same as the variables in the wage function, the selection problem will be:

$$E[\delta\varepsilon] \neq 0 \qquad (16)$$

[20] "Piece rate" is a unit price paid to the farm workers by the production of goods or services the workers provided during working hours.

[21] The quality-adjusted price of the purchased contracted labor service is to be used as the deflator of the total expense farm operators pay for the contract labor services. Therefore, the growth rate of the price for this service may not be comparable to the labor input, as the nature of these two inputs is not the same.

The error terms in equations (14) and (15) can be assumed with a joint normal error distribution to account for the selection bias as follows:

$$\begin{bmatrix}\varepsilon\\u\end{bmatrix} \text{iid} \sim \mathrm{N}\left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}\sigma^2 & \rho\\ \rho & 1\end{bmatrix}\right) \quad (17)$$

Expected wage rate by a contracted labor can be expressed as:

$$E[w_i|D_i = 1] = \boldsymbol{\beta}' x_i + \boldsymbol{\gamma}' \boldsymbol{z}_i + \delta + E[\varepsilon_i|D_i = 1] = \boldsymbol{\beta}' \boldsymbol{x}_i + \boldsymbol{\gamma}' \boldsymbol{z}_i + \delta + \rho\sigma\lambda_i \qquad (18)$$

where λ_i is the inverse Mills ratio. The parameters of the treatment-effects selection model are estimated using full maximum likelihood.

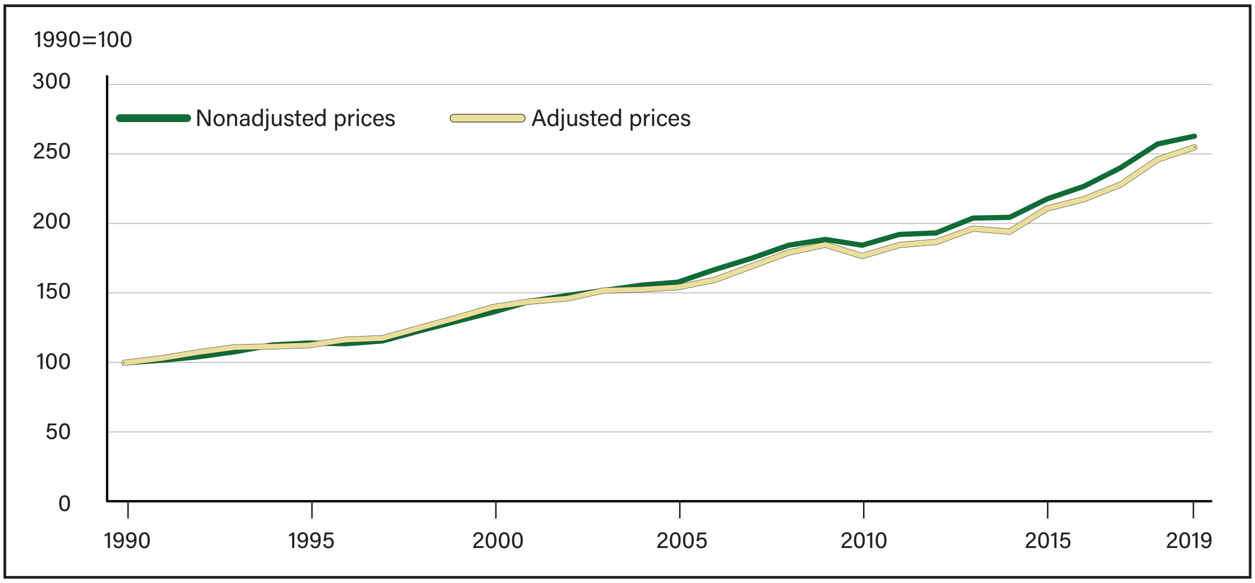
Data sources for contracted labor service

The data on the characteristics of farmworkers were drawn from NAWS. NAWS is a national, random sample of seasonal agricultural service (SAS) workers. NAWS uses stratified multistage sampling to account for seasonal and regional fluctuations in the level of farm employment. The interviews were conducted in 40 States and 467 counties. Workers are sampled from 12 regions and and data on workers have been collapsed into 6 production regions—East, Southeast, Midwest, Northwest, Southwest, and California.[22] The data cover the period 1989 to the present.

USDA, ERS constructed quality-adjusted prices for purchased contracted labor services at the national level, as well as for six production regions. Given the sample size limitation, USDA, ERS applied regional estimates in its State accounts instead of State estimates. Figure 6, panel A presents the comparison figures between quality-adjusted and unadjusted prices at the national level. After adjusting for demographic characteristics changes, the overall price changes for purchased contracted labor services have been slower than that of the unadjusted services, with both increasing more than 150 percent. Figure 6, panel B demonstrates the trend growth of quality-adjusted prices of purchased contracted labor services by region. Among the six regions, California ranked first in the relative level of the quality-adjusted price of purchased contracted labor services in 1989, with the Southwest region ranking last. The Southwest region has remained at the lowest level for more than 30 years, while the Northwest region surpassed California and became the highest price in 2019. While varying across regions, the estimated prices more than doubled between 1989 and 2019.

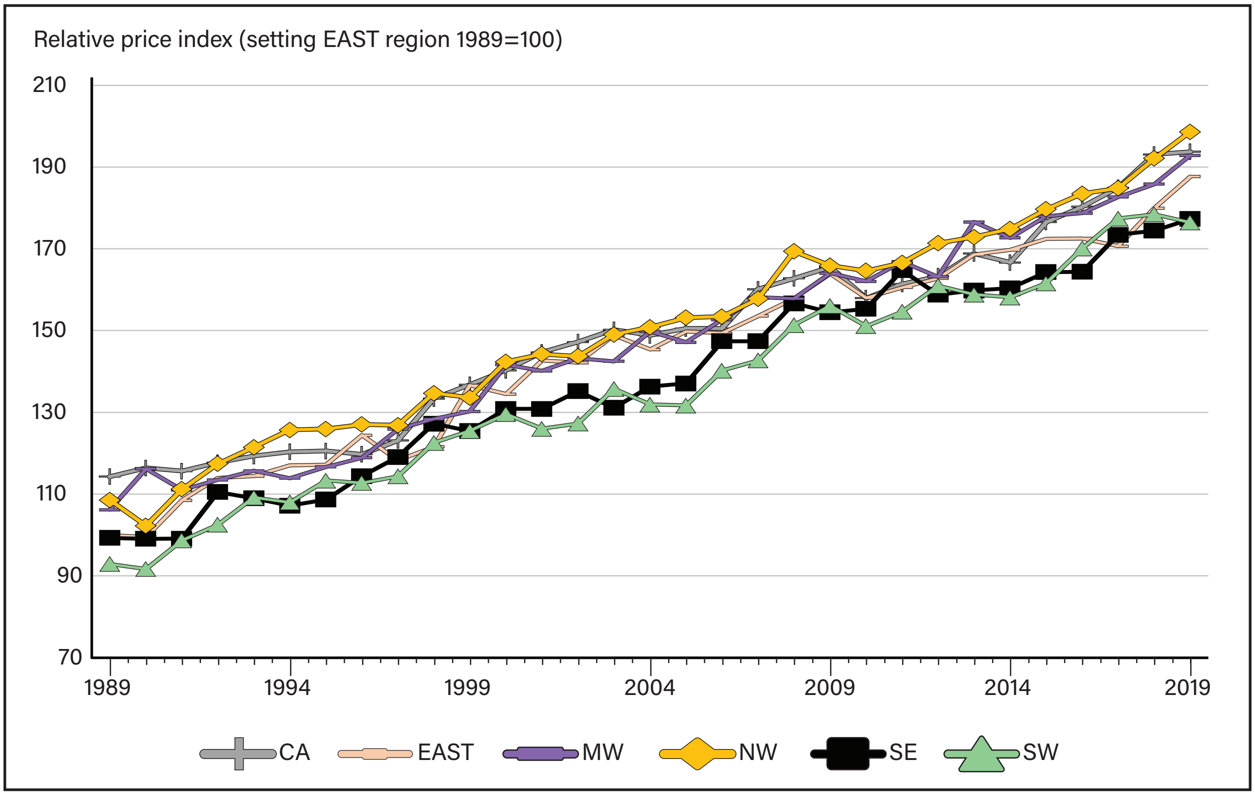
[22] The production regions are defined by the Employment Training Administration's National Agricultural Worker Survey and may be different from those defined by USDA. See the figure 6 note for States associated with each production region.

Figure 6a
Quality-adjusted and nonadjusted prices for purchased contracted labor services, 1989–2019



Source: USDA, Economic Research Service.

Figure 6b
Quality-adjusted prices for purchased contracted labor services varied across regions, 1989–2019



Note: CA=California; East includes Maine, New Hampshire, Vermont, Massachusetts, Connecticut, Pennsylvania, New Jersey, Delaware, Maryland, West Virgina, Virginia, Tennessee, and North Carolina; Midwest (MW) includes North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa, and Missouri; Northwest (NW) includes Washington, Oregon, Idaho, Montana, Nevada, Wyoming, Colorado, and Utah; Southeast (SE) includes Arkansas, Louisiana, Mississippi, Alabama, Georgia, Florida, and South Carolina; Southwest (SW) includes Arizona, New Mexico, Texas, and Oklahoma.

Source: USDA, Economic Research Service.

Labor Input

Total employment and total hours worked have been used as the measures of labor input in numerous empirical economic studies regarding productivity analysis. However, individual labor units are not homogenous, and the estimates of labor inputs that did not take into account changes in labor quality (due to differences in demographical characteristics) could result in biased TFP estimates. Following Jorgenson et al. (1987), we adopted the Törnqvist index number approach, with the same demographic classification method to construct quality-adjusted labor input indices for prices and quantities.

We assumed that labor input $\{L\}$ can be expressed as a translog function of its individual components, $\{L_l\}$, and the change of the labor estimate can be expressed as

$$ln\left(\frac{L_t}{L_{t-1}}\right) = \sum_l \frac{1}{2}(v_{lt} + v_{lt-1}) ln\left(\frac{L_{lt}}{L_{lt-1}}\right) \quad (19)$$

where *ln* indicates the natural logarithm function, $\frac{1}{2}(v_{lt} + v_{lt-1})$ is the average cost share of each labor group l—classified by their corresponding demographic characteristics—in two time periods, t and $t-1$. L_{lt} is the quantity (hours worked) of the l^{th} demographic group.

The matrices of employment, hours worked, and compensation per hour (for hired labor) were cross-classified by gender (male or female), age (eight groups), education (six categories; five categories before the year 1980), and employment class (hired versus self-employed or unpaid workers). Therefore, there were 192 (*i.e*, 2 x 8 x 6 x 2) demographic groups (160 groups for the data before 1980 due to changes made in the Census of Population survey regarding educational attainment) in constructing the Törnqvist indexes of labor input. Under the Törnqvist index specification, these indices reflect demographic changes in the composition of hours worked. For example, labor quality increased as components with higher compensation of labor input per hour grew more rapidly and fell otherwise. As a result, the price and quantity series for labor input were measured in constant-efficiency units, which were adjusted for compositional shifts.[23] Data on compensation, hours worked, and employment were drawn from the decennial Census of Population, American Community Survey, Current Population Survey, and BEA's National Income and Product Accounts. After the second review, we also incorporated American Community Survey microdata into the data sources to capture more concurrent intertemporal changes in demographic characteristics.

Under the translog approach, labor hours with higher marginal productivity (wages)[24] were given higher weights in forming the index of labor input than were hours having lower marginal productivities. This approach explicitly adjusted the time series of labor input for changes in the quality of labor hours, as originally defined by Jorgenson and Griliches (1967). As a result, the price and quantity series for labor input were measured in constant-quality units. If we represented those estimates in the form of a natural log, then the change in the quality-adjusted labor input (L^G) could be decomposed into the quality (Q^G) change and hours (quantity, H) change components as follows.[25]

$$\Delta ln L_t^G = \Delta ln Q_{L,t}^G + \Delta ln H_t \quad (20)$$

Over time, labor quantity has continued to decline in the U.S. farm sector, while labor quality has increased substantially. As a result, the quality-adjusted labor input did not decrease as fast as the labor hours used in the U.S. farm sector (figure 7). According to Wang et al. (2022), while the reduction of labor hours worked

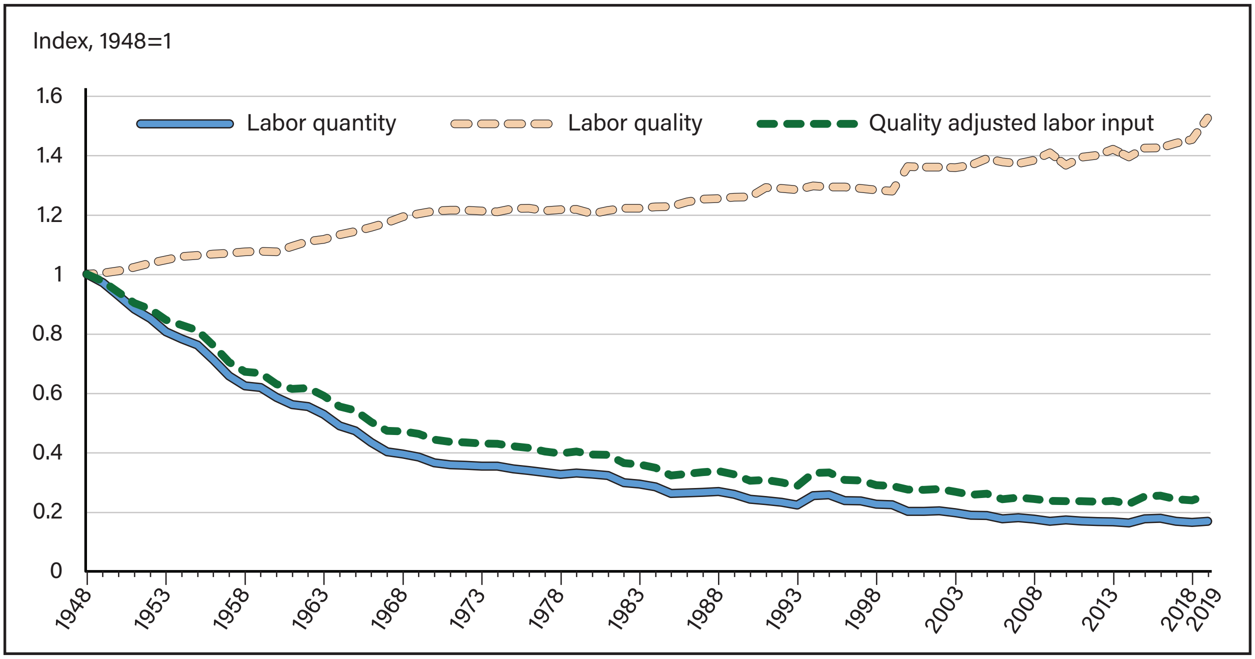
[23] JGF refers to the compositional shift as "quality" change.

[24] We assume labor is not homogeneous and the employer tends to pay more for those with higher productivity. Drawing data from the decennial Census of Population survey and the American Community Survey—as well as BEA and BLS data—we calculate hourly wage rates for each type of worker cross-classified by gender, age, educational attainment, and employment type.

[25] See Wang et al. (2022) for further disaggregation for the labor quality components.

contributed to -0.57 percentage points of annual output growth between 1948 and 2017, labor quality changes contributed to 0.11 percentage points of annual output growth on average that partially offset the negative effects of labor quantity decline.

Figure 7
Trends of growth of labor quantity, labor quality, and quality-adjusted labor input in the U.S. farm sector, 1948-2019



Source: USDA, Economic Research Service.

Land Input

Land productivity will depend greatly on the specific agro-ecological characteristics (Nehring et al., 2006; Ball et al., 2004) such as soil type, slope, among others, to account for spatial differences in land characteristics across 48 adjacent States in the State productivity accounts. Because of these characteristics, USDA, ERS constructed indices of relative prices of land across States for a specific year in its State accounts, using the hedonic regression method based on the following equation:

$$\ln\left(P_i^j\right) = \sum_{i=1}^{I} \delta_i D_i + \sum_{c=1}^{C} \beta_c X_{ic}^j + \varepsilon_{ij} \qquad i = 1, \ldots, I; c = 1, \ldots, C \qquad (21)$$

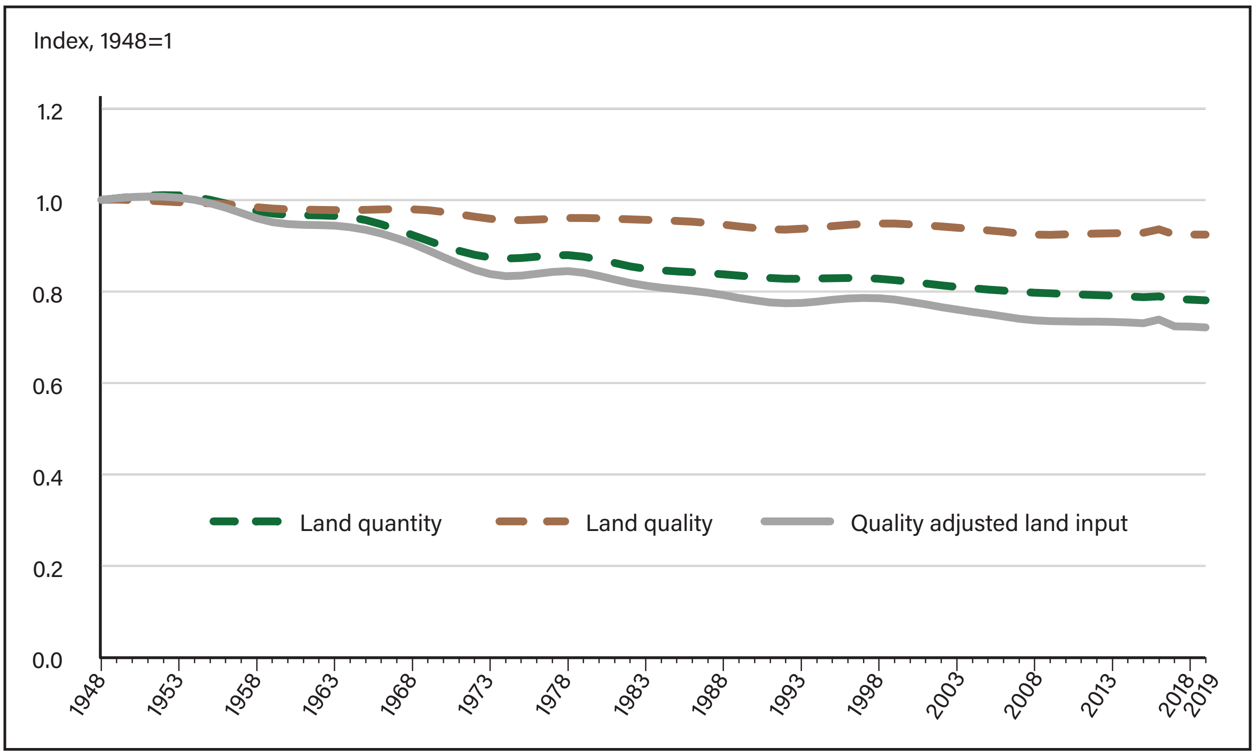
Where P_i^j is the price of land for county j in State i, X_{ic}^j are land characteristics for county j in State i, δ_i and β_c are parameters to be estimated, D_i is a State dummy variable, and ε_{ij} is a stochastic error term. The land characteristics were derived from climatic and geographic data in USDA's State Soil Geographic (STATSGO) database. The price of land was assumed to be a function of land characteristics (including soil acidity, salinity, and moisture stress, among others). Land characteristics data were drawn from the World Soil Resources Office of the USDA's Natural Resources Conservation Service (NRCS).

Since the soil characteristics data were not available annually and were assumed to be constant over time, the national land accounts are constructed following an index number approach. To obtain a constant-quality stock of land, we compiled data on acres of land in farms and the average value (excluding buildings) per acre. We assumed that land in each county is homogeneous; hence, aggregation is at the county level.[26] For each county in each State, we drew data from the Census of Agriculture. Data for years intermediate to the censuses were obtained by interpolation. We fitted a cubic spline in segmented function, consisting of third-degree polynomial functions joined together so that the entire curve and its first and second derivatives were continuous.

The land input in the aggregate sector (national accounts) was calculated by starting with the construction of State-level land stock, using a Törnqvist index number approach with county land values as the weights. State-level land stocks were then aggregated up again to the national level, using the Törnqvist index approach, with the State land value (excluding buildings) as the weights.

Over time, land acreages used in farm production have declined. The average land qualities for those remaining in the farm sector have also decreased but at a slower pace.[27] Urbanization and industrialization since World War II may have played a role in that development. Intensive agricultural practices over the years (such as conventional tillage) can likely be contributing factors (Su et al., 2021). As a result, the quality-adjusted land input contracted further in the U.S. farm sector (figure 8).

Figure 8
Trends of growth of land quantity, land quality, and quality-adjusted land input in the U.S. farm sector, 1948-2019



Source: USDA, Economic Research Service.

[26] These assumption and practices are due to data limitations. Using county-level data in our land measurement can at least help us capture land stock compositional shift across State and county boundaries over time. Expenses for land improvements can also help to increase the land prices that will be captured in land quality measurement.

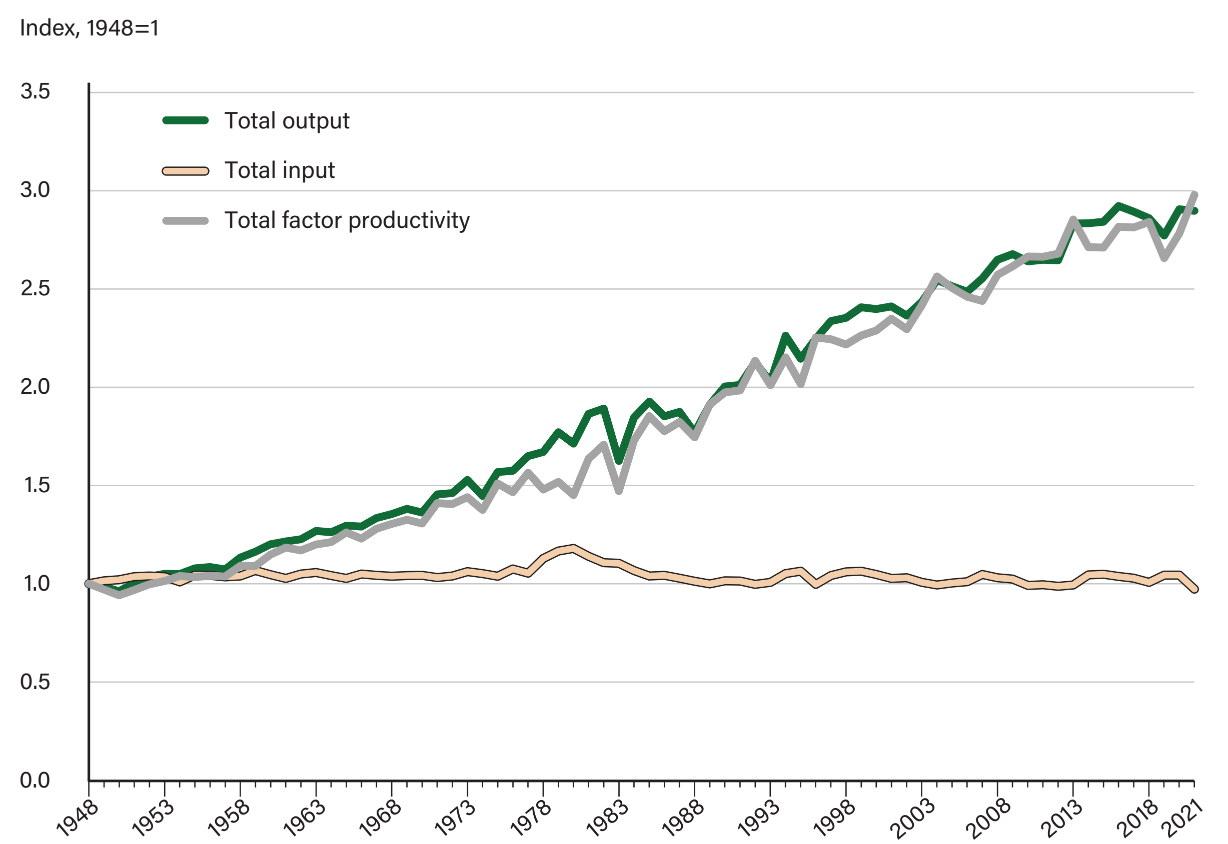
[27] Land near the urban area can have a higher price and be reallocated to nonagricultural uses more easily over time due to urbanization. Thus, farmland composition may shift from land with higher prices to that with lower prices in some areas.

Sources of U.S. Agricultural Growth Decomposition: Quantity Versus Quality Changes

Trends of Growth: Output, Input, and Total Factor Productivity

Output growth emanates from the growth of all input use (capital, land, labor, and intermediate inputs) and the growth of productivity (total factor productivity or TFP). According to USDA, ERS estimates, while total farm output grew by 190 percent over the full 1948–2021 period, total inputs used in agriculture reduced by 2 percent over the last seven decades. TFP growth measures output growth that cannot be explained by growth in inputs, such as innovations in farm tasks, changes in the organization and structure of the farm sector (O'Donoghue et al., 2011; MacDonald et al., 2016), improvements in animal and crop genetics, or other embodied and disembodied technical changes. Between 1948 and 2021, farm output grew at 1.46 percent per year on average. With total input (including land, labor, capital, and intermediate inputs) declining by -0.03 percent per year, TFP (an indicator of overall technology advancement) grew at 1.49 percent per year, single-handedly leading farm output to grow 190 percent above its 1948 level (figure 9). There are many driving factors behind the long-term trend growth of TFP (such as research and development, public infrastructures) and short-term TFP variations (such as adverse weather) that require our attention and understanding in order to pursue sustainable agricultural growth (for more discussion see Schlenker, 2019; Wang et al., 2015; Fuglie et al., 2012; Alston et al., 2010; and Huffman & Evenson, 2006).

Figure 9
Trends of growth of output, input, and total factor productivity, 1948–2021

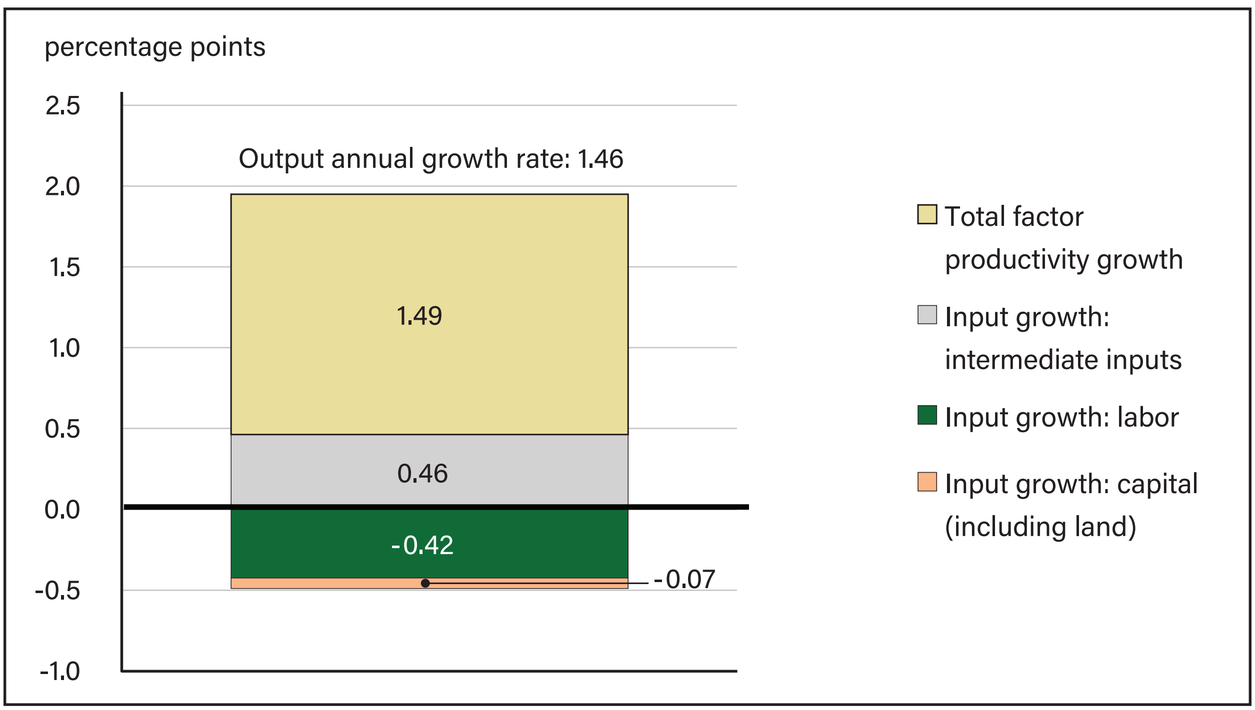


Source: USDA, Economic Research Service. "Agricultural Productivity in the U.S." data, January 2024 release.

Sources of Growth: Inputs Versus TFP

Under the growth accounting framework, the economic growth of the U.S. agricultural sector could be decomposed into input growth—growth of labor, capital (including land), and intermediate inputs—and TFP growth (Jorgenson et al., 2005). While total input grew slightly, its composition has changed markedly. Farm input composition has gradually shifted from labor and land toward machinery and intermediate input. This shift has occurred along with the economic expansion in the nonagricultural sectors that pulled away some labor and land from the farm sector and technological advancements that made machinery and other production materials (such as fertilizer and pesticides) more affordable to farm operators. Between 1948 and 2021, labor and land inputs declined by 76 and 28 percent, respectively, while intermediate input grew by 109 percent. Thus, the sources of growth changed over time. For example, in the immediate post-World War II period (1948–53), annual input growth contributed to two-thirds of the annual output growth during the period—one of the only two periods in which input growth contributed more than TFP growth[28] (table 1). Nevertheless, TFP has played the majority role in promoting output growth in most of the years between 1948 and 2021. On average, TFP growth contributed 1.49 percentage points to the annual output growth of 1.46 percent, while intermediate input contributed 0.46 percentage points. Due to the decline in labor and land use, the annual growth rates of labor and capital inputs contributed negatively to annual output growth on average (figure 10).

Figure 10
Agricultural output growth decomposition, 1948–2021



Source: USDA, Economic Research Service, "Agricultural Productivity in the U.S." data, January 2024 release.

[28] The other one was the 1973–79 period.

Table 1

Sources of growth decomposition (average contribution to annual output growth rates in percentage points)

	1948–2021	1948–1953	1953–1957	1957–1960	1960–1969	1969–1973	1973–1979	1979–1981	1981–1990	1990–2000	2000–2007	2007–2019	2019–2021
Output growth	1.46	0.98	0.54	3.75	1.56	2.54	2.45	2.57	0.80	1.80	0.90	0.68	2.23
Sources of growth decomposition													
Input growth	-0.03	0.67	-0.01	0.34	-0.04	0.49	1.55	-1.25	-1.28	0.30	0.08	-0.02	-3.35
Labor	-0.42	-0.83	-1.11	-0.88	-0.79	-0.41	-0.19	-0.23	-0.45	-0.23	-0.37	0.38	-1.65
Capital	-0.07	0.57	0.00	-0.12	0.06	-0.15	0.30	0.04	-0.76	-0.22	-0.05	0.06	-0.10
Intermediate input	0.46	0.92	1.10	1.34	0.68	1.06	1.44	-1.05	-0.07	0.75	0.50	-0.46	-1.60
Total factor productivity	1.49	0.31	0.55	3.41	1.60	2.04	0.90	3.82	2.08	1.49	0.82	0.70	5.57
Input-growth decomposition													
Labor	-0.42	-0.83	-1.11	-0.88	-0.79	-0.41	-0.19	-0.23	-0.45	-0.23	-0.37	0.38	-1.65
Hours	-0.53	-1.06	-1.24	-0.92	-1.08	-0.46	-0.21	-0.20	-0.52	-0.40	-0.40	-0.20	0.07
Quality	0.11	0.23	0.12	0.04	0.29	0.05	0.01	-0.03	0.07	0.18	0.02	0.58	-1.72
Capital	-0.07	0.57	0.00	-0.12	0.06	-0.15	0.30	0.04	-0.76	-0.22	-0.05	0.06	-0.10
Stocks	-0.10	0.19	-0.18	-0.20	-0.12	-0.36	0.14	-0.13	-0.34	-0.09	-0.13	-0.03	-0.07
Quality	0.04	0.37	0.18	0.08	0.18	0.21	0.16	0.17	-0.42	-0.13	0.08	0.09	-0.03
Intermediate inputs	0.46	0.92	1.10	1.34	0.68	1.06	1.44	-1.05	-0.07	0.75	0.50	-0.46	-1.60
Quantity	0.43	1.04	0.90	1.24	0.63	1.08	1.55	-1.35	-0.20	0.76	0.44	-0.50	-1.62
Quality	0.04	-0.12	0.20	0.10	0.05	-0.02	-0.12	0.30	0.13	-0.02	0.06	0.04	0.02

Note: The subperiods are measured from cyclical peak to peak in aggregate economic activity.

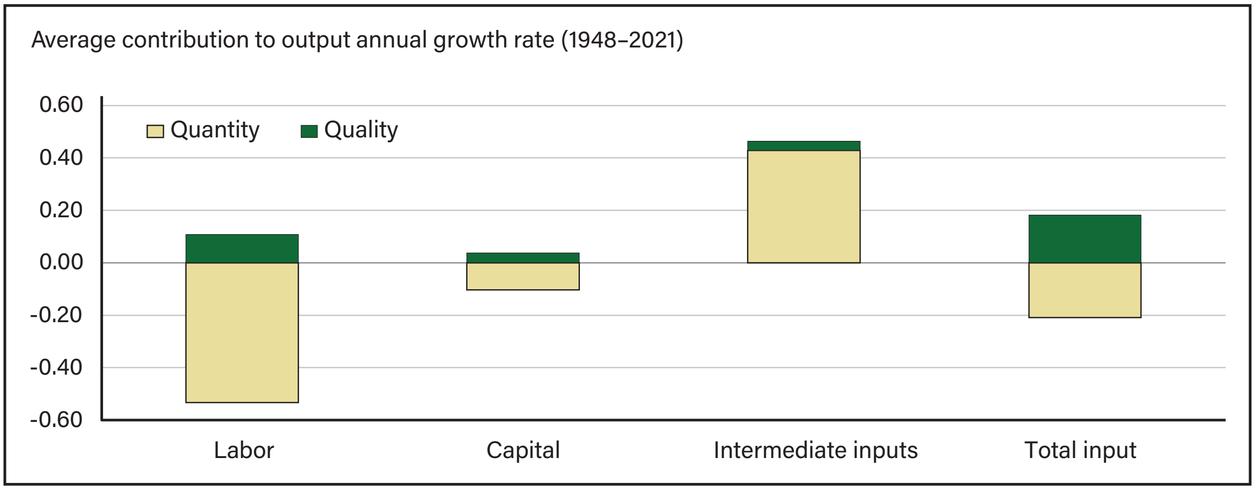
Each input factor's contribution to the output growth rate in a specific period is calculated as its average growth rate weighted by its average input-cost-share in that period. All values are rounded to two decimal places. Therefore, an individual input's contribution to output growth may not equal exactly the sum of the quantity and quality contribution values.

Source: USDA, Economic Research Service, "Agricultural Productivity in the U.S." data, January 2024 release.

Sources of Input Growth: Quantity Versus Quality

The negative contributions of labor and capital were all the more notable given the positive contributions offered through improvements in both labor and capital quality (figure 11), the recomposition of demographic characteristics in the labor hours worked, and the shifting use of the types of capital assets in total capital stocks. As shown in figure 11 and table 1, farms have shifted to higher quality labor (i.e., a more-educated labor force, see Wang et al. (2022) for further discussion). Along with the reduction of land use, farms rely more on machinery use with higher productivity in the capital category. Differing from labor and capital inputs, intermediate inputs have increased more in quantity (volume) than in quality changes (composition shift) over time. Between 1948 and 2021, annual farm quantity and quality growth in intermediate inputs contributed to annual output growth by 0.43 and 0.04 percentage points, respectively.

Figure 11
Input-growth decomposition: Quality versus quantity, 1948–2021



Source: USDA, Economic Research Service. "Agricultural Productivity in the U.S." data, January 2024 release.

Major Changes Since the 2014 Review and Working Projects

Shumway et al. (2017) made a variety of recommendations in their review of the U.S. agricultural productivity statistics program in 2014. Some major recommendations included the overarching concerns of documentation and efficiency, website communication of methods and data, measurement of inputs and outputs, and new data sources, as well as the renewal of State accounts. USDA, ERS has made several major changes since the review. In this section, we document some changes incorporated in the U.S. agricultural productivity measurement since the 2014 external review, along with future research plans that address the recommendations in the review.

Major Changes

Data Documentation, Efficiency, and Website Documentation

USDA, ERS researchers have revised the data website by incorporating more details regarding the methodologies, updates and revision history, and findings, as well as the website's uses and publications, among other updates. Measured statistics are reported in both Excel and CSV formats.

There are a few major changes regarding the measurement and data sources, as follows:

- **Capital:** We introduced the use of asset-specific rates of price inflation when measuring the user cost of capital input in the national accounts.
- **Labor:** We incorporated the American Community Survey as a part of data sources in labor estimates and replaced the self-employed and unpaid worker data from the USDA, Farm Labor Survey[29] (FLS) with ARMS data in the State accounts (using 2002, the last year of the available data, as the benchmark).
- **Intermediate inputs and outputs**: Purchases of livestock were not included in intermediate inputs, as the purchases were in previous releases. Rather, purchases of these animals represent "goods in progress." Therefore, acquisitions were recorded as additions to stocks, while the cost of livestock purchases was deducted from livestock receipts.

Working Projects and Future Development

USDA, ERS researchers have been conducting studies independently or in collaboration with other Federal statistical agencies or universities to address recommendations made by Shumway et al. (2017) and other emerging topics. Once the results of the following projects are properly reviewed, the results will be incorporated into future U.S. agricultural productivity accounts. While output quality adjustment was recommended by Shumway et al., due to data limitation, we were not able to adjust for output quality for each commodity back to 1948, the starting point of the national productivity accounts. However, in our output measurement, we tried to use as much disaggregated data as possible to account for a composition shift within a category or subcategory. Capturing a compositional shift among commodities over a long period of time can also be seen as a sort of "quality adjustment" within a category or subcategory of output, as in the input measurement. Ongoing projects for improving the national productivity accounts include but are not limited to:

(1) **The measurement of biological capital assets:** Biological capital involves cultivated plants and animals that provide productive services for more than one production period, such as breeding stock and perennial crops and orchards. While some biological capital assets have been incorporated into the U.S. agricultural productivity accounts in the form of "inventory" (Ball et al., 2016) Shumway et al. (2017) recommended that USDA, ERS adopt a more sophisticated method and more detailed data to measure biological capital assets in the U.S. productivity measurement. The objective of this project was to develop measures of biological capital stock, as well as their rental rates, to be used in the U.S. agricultural productivity accounts.

(2) **Measurement of quality-adjusted seed prices:** Modern agricultural biotechnology has facilitated the development of biological innovations embodied in new seeds, contributing to sustained agricultural productivity growth and helping to ensure an abundance of food and fiber (Fernandez-Cornejo et al., 2004). Genetically engineered seed varieties with pest management traits became commercially available for major crops (corn, soybeans, and cotton) in 1996. USDA, ERS researchers are conducting

[29] The self-employed and unpaid worker questionnaire was terminated after 2002, while the hired worker questionnaire is sustained in the FLS.

hedonic pricing analysis of seed traits for corn, cotton, rice, wheat, and soybeans (Nehring et al., 2023). The final results will be quality-adjusted prices and quantities of seed input.

(3) **Development of the State productivity accounts.** While the national data series has been updated through 2021, State-level statistics were suspended due to the discontinuance of critical labor data. This project revisits the State productivity measurement issues by introducing a new labor data source to develop a quality-adjusted State labor panel. We plan to construct panels of inputs, outputs, and total factor productivity for the 48 contiguous States after incorporating the new State labor accounts.

In addition to these specific projects, USDA, ERS researchers will continuously improve our current measurement in adjusting for input quality changes, including but not limited to hedonic regression model specification and data sources.

Changes With Each Data Release Since the 2014 Review

On the USDA, ERS "Agricultural Productivity in the U.S." data page, we document changes with each data release. Some changes since the 2014 review are listed below.

January 12, 2024

Updated 1948–2021 U.S. productivity statistics were released; we extended the national agricultural productivity accounts to 2021. Some historical estimates of prices, quantities, and total factor productivity were revised to reflect changes made in source data, including USDA, Economic Research Service; USDA, National Agricultural Statistics Service; U.S. Department of Commerce, Bureau of Economic Analysis; and U.S. Department of Labor, Bureau of Labor Statistics. We also drew land improvement data from the USDA's Agricultural Resource and Management Survey. The land improvement estimates are now incorporated in both the input quantity and output quantity measures in the U.S. national productivity accounts, as recommended by Shumway et al. (2017). Lastly, we modified the business cycle dating to be consistent with changes made by the National Bureau of Economic Research.

January 6, 2022

Updated 1948–2019 U.S. productivity statistics were released; we extended the productivity accounts to 2019. Some historical estimates of prices, quantities, and total factor productivity were revised to reflect changes made to data sources. These sources include USDA, ERS; USDA, NASS; U.S. Department of Commerce, Bureau of Economic Analysis (BEA); and U.S. Department of Labor, Bureau of Labor Statistics (BLS).

January 10, 2020

Updated 1948–2017 U.S. productivity statistics were released; we extended the productivity accounts to 2017. There were two major changes with this revision. First, we changed the index year from 2005 to 2015, so the implicit quantity measures are in 2015 dollars. Second, we changed the way we measure inventory rental prices[30] and data sources for data consistency. In addition, historical data were revised when there was a revision in our source data, including the changes made by USDA, NASS; USDA, ERS; BEA; and BLS.

October 10, 2017

[30] The rental price is the product of the inventory price and the expected real rate of return (see the Capital section above). The real rate of return is the difference between the nominal interest rate and the rate of inflation, measured by the implicit deflator for gross domestic product instead of the inventory inflation rate in this revision, in order to smooth the series and for data consistency.

Updated 1948–2015 U.S. productivity statistics were released; we extended the productivity accounts to 2015. Historical data were revised when there was a revision in our source data. Some output and input series were revised as far back as 1948 for consistency. These revisions were done to reflect the changes made by USDA, NASS; USDA, ERS; BEA; and BLS. For example, some changes reflect revisions in cash receipts, inventory changes, and production expenses made by USDA, NASS and USDA, ERS, or labor estimates reported by BEA or BLS.

September 21, 2016

Revisions were made to the "Methods" chapter, content was added to a new "Update and Revision History" chapter, and the chapter "Uses and Publications" section was added.

December 14, 2015

Updated 1948–2013 U.S. productivity statistics were released. Changes made with this revision include data sources and measurement and were as follows:

To reflect the changes made by our data sources (such as USDA, NASS; USDA, ERS; BEA; and BLS), some output and input data were revised back as far as 2000. In addition, methodologies for capital measurement and purchases of livestock were changed with this release, and some input estimates were revised back to 1948 when data were available, for consistency.

Changes in the measurement of labor input were necessitated by the adoption of new sources for data on employment, hours worked, and compensation per hour. Our original data source (the Farm Labor Survey document administered by USDA, NASS) was discontinued. The data on self-employed and unpaid family workers are now taken from the decennial Census of Population and the annual Current Population Survey. The BEA's National Income and Product Accounts (NIPA) product is the source for data on employment, hours worked, and compensation of hired farm workers. The adoption of the new data sources has allowed us to extend our estimates of labor input (and hence productivity) through 2013 but has also required that we revise these series for prior years. In addition, the American Community Survey (ACS), which was fully implemented in 2005 by the Census Bureau, is now part of the Decennial Census Program and has replaced the long-form sample questionnaire of the Census of Population. Therefore, we now rely on ACS microdata rather than the decennial Census of Population in developing estimates of labor input.

The share of purchased contract labor services in total production cost has increased over time in U.S. farm production. Since farmers typically contract with labor brokers to assemble crews, there is a scarcity of data on farm hours worked. Only data on nominal expenditures for contract labor are collected. In order to account for the contribution of contract labor services to output growth, we must construct an appropriate deflator for these expenditures. Since the compensation of contract workers will likely vary with differences in demographic characteristics such as age, experience, gender, and education, we constructed a deflator for contract labor using hedonic methods based on data from the National Agricultural Workers Survey.

In this release, purchases of livestock have not been included in intermediate input as the purchases were in previous releases. Rather, these animals represent "goods in progress." Acquisitions were thus recorded as additions to stocks, while the cost of livestock purchases was deducted from livestock receipts.

We also introduced changes in the way we measure capital input. There has been a longstanding debate over whether an ex-post or ex-ante measure of the user cost of capital should be used in growth accounting. In the ex-post approach (see, for example, Jorgenson & Griliches, 1967; Christensen & Jorgenson, 1969; Jorgenson et al., 1987), it is assumed that the rate of return is equalized across assets. Then this unknown rate can be found by using the condition that the sum of returns across assets (where the return on an asset is the product of its user cost and the flow of services it yields) equals observed gross profits. The alternative, ex-ante approach (see Coen, 1975; Penson et al., 1977; Diewert, 1980; Romain et al., 1987; Ball et al., 2008) employs a rate of return derived from financial market data, together with estimates of expected rather than actual asset price inflation. We adopted the latter approach; the ex-ante rate was calculated as the nominal yield on investment-grade corporate bonds adjusted for expected rather than actual price inflation. We introduced the use of asset-specific rates of price inflation, as recommended by Shumway et al. (2017). Earlier (see Ball et al., 1999), the USDA used a broad measure of inflation (the implicit deflator for gross domestic product) to calculate the real rate of return based on the theory that expected real rates of return should be equal across all assets.

Our estimates of the stock of land are based on county-level data on land area and value obtained from the Census of Agriculture. Data for the inter-census years were obtained through interpolation using spline functions. The Census reports the value of farm real estate (i.e., land and structures), as opposed to the value of land. Historically, the value of farm real estate was partitioned into components using information from the USDA Agricultural Economics and Land Ownership Survey (AELOS). However, the AELOS was last published in 1999. More recently, we have relied on data from the annual USDA, Agricultural Resource Management Survey (ARMS) to partition real estate values into its components.

Pesticides and fertilizer are important intermediate inputs, but their data require adjustment since these inputs have undergone significant changes in input quality over the study period. Since input price and quantity series used in a study of productivity must be denominated in constant-efficiency units, we constructed price indices for fertilizers and pesticides from hedonic regression results. The corresponding quantity indices are formed implicitly as the ratio of the value of each aggregate to its price index.

Finally, we reported price indices and implicit quantities (i.e., values of expenditures at constant 2005 prices) of the economic aggregates (e.g., output; capital; labor; intermediate goods); see the tab for table 1a for national data and table 23 for State data in the Agricultural Productivity in the United States data. The data can be used for both time series and cross-section analysis.

Conclusion

The advancement of U.S. agricultural productivity is essential to maintaining sustainable agricultural growth and food security. USDA, ERS has been monitoring the U.S. farm sector's productivity performance since the 1960s, using a total factor productivity measure. This report provides detailed information on how USDA, ERS measures outputs, inputs, capital (including land, labor, and intermediate inputs), and total factor productivity in its U.S. agricultural productivity accounts. Since input qualities are likely to vary over time, it is important to measure inputs in their constant qualities, especially for data spanning a long period of time (the current U.S. productivity accounts cover the period 1948–2021). This report describes in detail on how USDA, ERS accounts for input quality changes in its input measurement—such as fertilizer, pesticides, purchased contracted labor services, labor, and land.

According to the measurement, the major driver of U.S. agricultural growth is total factor productivity growth. Between 1948 and 2021, total U.S. farm output grew by 1.46 percent per year. With total inputs (including land, labor, capital, and intermediate inputs) declining by -0.03 percent annually, total factor productivity grew at 1.49 percent per year, single-handedly driving farm output growth over the seven-decade period. In 2021, total output was about 2.9 times its 1948 level. During this period—input quality changes in labor, capital (including land), and intermediate inputs (such as fertilizer, pesticides, and purchased services)—contributed positively to annual output growth by 0.11, 0.04, and 0.04 percentage points, respectively. TFP growth would be overstated if we did not account for input quality changes.

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