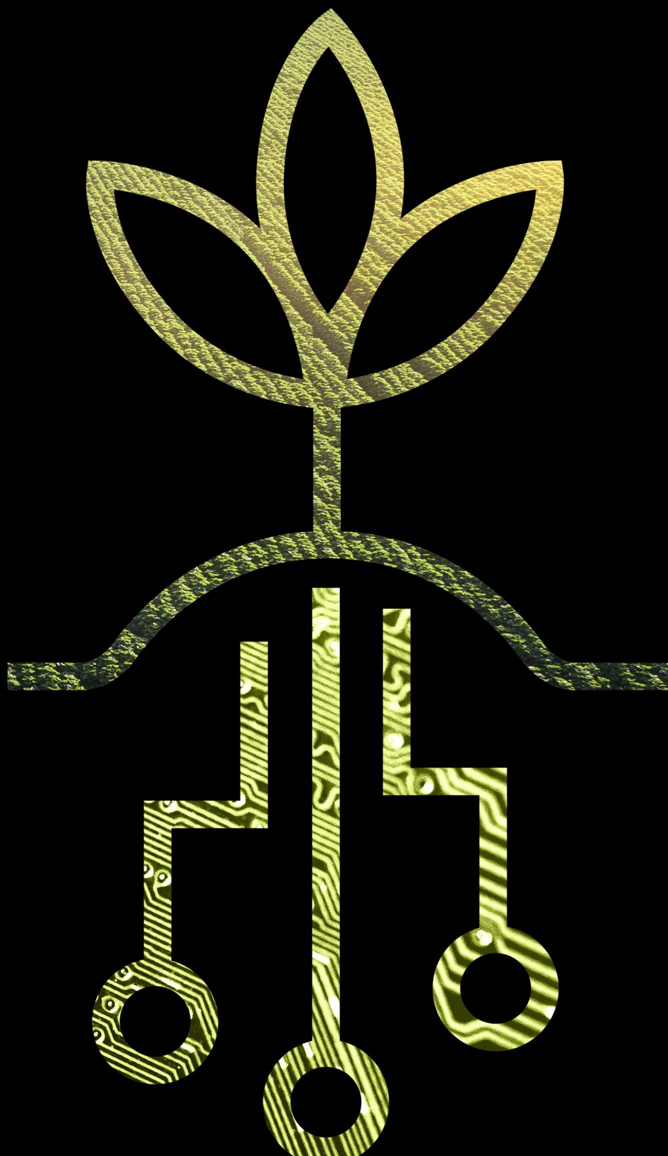

THE ROOTS OF AGRICULTURAL PRODUCTIVITY GROWTH

2020 Agricultural Symposium: The Roots of Agricultural Productivity Growth

Foreword

For many years, farm production has been on the rise, as agricultural producers have capitalized on technological innovations and modernized farming practices. These gains have been important in meeting the needs of a growing global population. Still, producers face challenges. An important one emerged this year, as the COVID-19 pandemic not only created the potential for constraints to productivity growth but also fostered an economic slowdown. While it is premature to judge the pandemic's longer-term effects, it is likely to leave its mark on the road ahead.

The Federal Reserve Bank of Kansas City had intended to host an Agricultural Symposium this year titled "The Roots of Agricultural Productivity Growth," but ultimately made the difficult decision to cancel due to the pandemic. The topic of productivity growth, and the papers that were written in anticipation of the 2020 symposium, remain relevant.

For that reason, we are publishing these papers to help inform future discussions. The papers explore historical factors driving agricultural productivity growth, the role of technology adoption, connections to other segments of the agricultural supply chain, and the influence of environmental factors. As circumstances connected to this year's pandemic continue to evolve, it is my hope that these papers will provide a useful foundation for understanding how agricultural productivity may determine longer-term prospects in the agricultural sector of our economy.

Esther L George

President and Chief Executive Officer
Federal Reserve Bank of Kansas City

The Drivers of U.S. Agricultural Productivity Growth

Philip G. Pardey and Julian M. Alston

Over the past 100 years, productivity growth in U.S. agriculture radically reshaped the country's farm sector and its role in the national economy. In 1900, agricultural output constituted 15.5 percent of U.S. GDP, and it took 5.7 million U.S. farms and 37.9 percent of the national labor force to feed and clothe 76 million U.S. consumers: a consumer-to-farmer ratio of 13:1. By 2017, agriculture had shrunk to 0.9 percent of GDP and the farm labor force to 1.1 percent of the national total. While the number of U.S. consumers had grown to 325 million, the number of farms had shrunk to just 2.0 million, increasing the consumer-to-farmer ratio to 159:1.

U.S. agricultural output increased, in aggregate, 4.6-fold from 1910 to 2007.[1] The mixture of inputs changed dramatically. U.S. farms now use greater quantities of purchased inputs (such as seed, energy, and chemicals) than they did a century ago and much less labor: labor use in agriculture fell by 80 percent. With these opposing trends

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balancing each other, aggregate input use overall increased little (Alston and Pardey 2020). Hence, multifactor productivity (MFP)—the aggregate output relative to the aggregate of measured inputs—increased 3.5-fold, growing on average by 1.42 percent per year from 1910 to 2007.

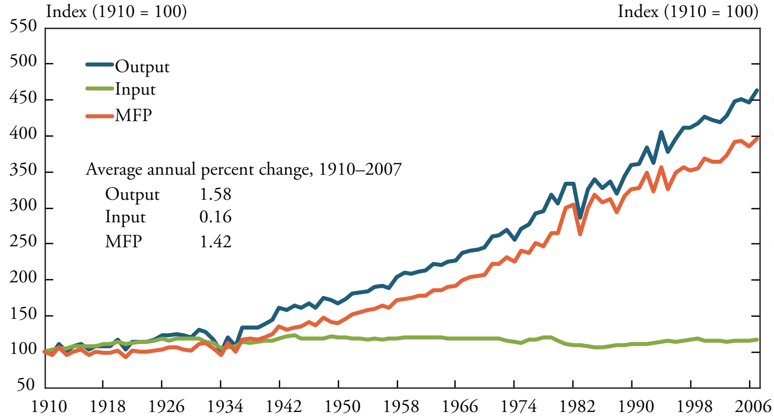
How can U.S. agriculture now produce so much more output per year with little overall change in the measured use of inputs? The story is complicated. Fundamentally, major labor- and land-saving innovations and the associated structural transformation of agriculture were facilitated by public and private investments in research and development (R&D) and incentivized by changes in the broader economy. But these processes involved complex cause-and-effect relationships that are hard to disentangle.

Our account of the drivers of long-term productivity growth in U.S. agriculture focuses first on the direct role of R&D-driven growth through the stock of scientific knowledge.[2] We then turn to the roles of technological innovation and the structural transformation of agriculture—farm size, specialization, what crops are grown where and when, how resources are used, and the roles of off-farm employment and part-time farming. We highlight the uneven evolving time path of U.S. agricultural productivity—in particular, a significant midcentury surge followed by a slowdown—which helps us as we try to identify the relative roles of different drivers at different times. We conclude the paper by considering the prospects for U.S. farm productivity growth in the face of emerging economic and environmental headwinds.

I. The Long-Run Pattern of MFP Growth

From 1910 to 2007, the index of the aggregate quantity of output (Q) grew at an average rate of 1.58 percent per year. Meanwhile, the index of the aggregate quantity of inputs (X) used in U.S. agriculture grew by just 0.16 percent per year, reflecting some increases in inputs of capital and materials that offset the reductions in the use of land (after the late 1970s) and especially labor. Consequently, the measure of MFP ($MFP = Q/X$) grew at a long-run average rate of 1.42 percent per year (Chart 1). This implies that U.S. agriculture produced 4.6 times as much aggregate output in 2007 as in 1910, without appreciably increasing the quantity of aggregate input.

Chart 1
Quantity Indexes of Output, Input, and MFP, U.S. Agriculture, 1910–2007



Source: Abridged version of Figure 1 in Pardey and Alston (forthcoming).

The long-run path was not always smooth—secular changes in productivity growth are confounded with year-to-year variations related to weather and other transitory factors. Table 1 shows growth rates in U.S. MFP by decade for the period 1910–2007. Rates of MFP growth have varied considerably from decade to decade, with relatively high rates of growth during the period 1950–80—when the rate of growth of aggregate output was also relatively high—and relatively slow rates of growth since then.

Using essentially the same data, Andersen and others (2018) estimate various trend models and strongly reject the hypothesis of a constant growth rate. Their results support the view that U.S. farm productivity growth has slowed in recent decades, but they also suggest that this slowdown came after a period of unusually rapid productivity growth. MFP grew by 1.42 percent per year for 1910–2007, but this long-term average reflected a period of below-average growth at 0.83 percent per year for 1910–50, above-average growth at 2.12 percent per year for 1950–90, and again below-average growth at 1.16 percent per year for 1990–2007.

Using state-specific and regional data for the period 1949–2007, Table 2 reveals that higher-than-average rates of output growth in some regions (for example, the Pacific and Northern Plains regions) were associated with correspondingly higher-than-average growth rates of

Table 1
Annual Average U.S. Farm and Nonfarm Private Business MFP Growth Rates, 1910–2007

Period	Private business sector MFP growth		Agricultural GDP as a share of GDP	Farm labor share of total
	Nonfarm	Farm		
	(percent per year)		(percent)	(percent)
1910–20	1.61	0.21	15.8	27.4
1920–30	1.56	-0.07	9.9	23.1
1930–40	2.52	1.71	7.5	22.9
1940–50	2.05	1.47	7.3	15.9
1950–60	1.31	2.25	4.8	10.8
1960–70	1.76	1.69	2.8	6.6
1970–80	0.88	2.46	2.5	4.1
1980–90	0.55	2.08	1.7	2.7
1990–2000	0.97	1.25	1.3	1.7
2000–07	1.39	1.03	1.0	1.4
1910–50	1.93	0.83	10.2	22.3
1950–2007	1.13	1.83	2.4	4.8
1910–2007	1.46	1.42	5.6	12.0

Notes: All MFP growth rates represent averages of annual (year-over-year) rates for the respective periods calculated by the log-difference method. Labor includes the number of full-time equivalent employees plus the number of self-employed persons and unpaid family workers. Shading indicates the decades with growth rates above the long-term (1910–2007) average.
Source: Abridged version of Table 2 in Pardey and Alston (forthcoming).

input use. The Pacific, Northern Plains, and Southern Plains regions recorded somewhat higher regional productivity growth rates; the Central, Mountain, and Northeast regions somewhat lower. However, each region experienced solid productivity growth on average during the period 1949–2007—average annual productivity growth ranged between 1.54 and 2.05 percent per year among regions—and a slowdown.

The regions and states within them are quite diverse in relevant respects. In the Northeast, input use shrank considerably while output grew comparatively little. For the Southeast, Central, and Southern Plains regions, aggregate input use also declined against solid output

Table 2
Regional and National Input, Output, and Productivity Growth Rates, 1949–2007

Region	1949–2007					MFP by decade					
			MFP			1949–	1960–	1970–	1980–	1990–	2000–
	Input	Output	Mean	Min.	Max.	60	70	80	90	2000	07
	(percent per year)										
Pacific	0.54	2.32	1.79	1.66	1.95	1.26	2.29	3.10	1.48	1.15	1.36
Mountain	0.48	1.68	1.20	0.49	2.05	1.55	1.72	1.60	1.46	1.13	-0.92
Northern Plains	0.15	2.20	2.05	1.75	2.36	2.76	1.27	1.65	3.60	1.28	1.46
Southern Plains	-0.21	1.82	2.03	1.16	2.94	2.08	2.63	2.09	2.29	1.40	1.56
Central	-0.24	1.38	1.61	1.32	1.90	1.40	1.03	2.77	1.67	1.48	1.23
Southeast	-0.46	1.26	1.72	0.97	2.69	2.07	2.00	2.74	2.42	0.74	-0.27
Northeast	-1.08	0.46	1.54	1.03	2.22	2.75	2.74	0.94	2.01	-0.29	0.67
United States	-0.07	1.70	1.77	1.77	1.77	1.89	1.69	2.46	2.08	1.25	1.03

Notes: All growth rates represent averages of annual (year-over-year) rates of the respective periods calculated by the log-difference method. Shading indicates the decades when growth rates peaked. The regions are as follows: Pacific—California, Oregon, Washington; Mountain—Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming; Northern Plains—Kansas, Nebraska, North Dakota, South Dakota; Southern Plains—Arkansas, Louisiana, Mississippi, Oklahoma, Texas; Central—Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Ohio, Wisconsin; Southeast—Alabama, Florida, Georgia, Kentucky, North Carolina, South Carolina, Tennessee, Virginia, West Virginia; Northeast—Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont.
Source: Calculated by the authors using Version 5 of the InSTePP Production Accounts.

growth (albeit much less than in the Northeast). In the other regions both inputs and outputs grew, and for the Pacific region MFP growth reflected greater-than-average input growth but even greater output growth. The timing of the surge in MFP growth varied among regions. In the Northeast and Southern Plains regions, MFP growth peaked a decade or two ahead of the national peak in the 1970s, shared with the Pacific, Central, and Southeast regions; in the Northern Plains, it peaked a decade later, in the 1980s.

Agricultural and economy-wide MFP growth

During the first half of the twentieth century, relatively rapid growth of the nonfarm sector came partly at the expense of the farm sector—especially by attracting labor away from farms—with implications both for labor-saving innovations on farms and the growth rate of farm productivity as well as for the farm share of the total economy (Kendrick and Jones 1951). In the early 1900s, agriculture employed more than one-third of the national workforce: rural-urban migration mattered, and changes in agricultural productivity had meaningful effects on national productivity measures. By the early 2000s, agriculture's share of the economy had shrunk to the extent that changes in agriculture had little consequence for economy-wide measures of economic performance.[3]

These connections are reflected in the measures of U.S. farm and nonfarm private business MFP growth reported in Table 1. The long-term (1910–2007) annual average MFP growth rate for the farm sector was 1.42 percent per year. However, during the period 1910–50, MFP grew in the nonfarm sector by 1.93 percent per year on average, more than twice the rate for the farm sector, 0.83 percent per year. And for 1950–2007, these roles were reversed: MFP grew by 1.83 percent per year in the farm sector but just 1.13 percent per year in the nonfarm sector.

Table 1 shows that U.S. nonfarm productivity growth accelerated in the 1910s and 1920s, peaked in the 1930s and 1940s, and began to slow appreciably in the 1950s, with a sharp drop in the 1970s. Hence, for the nonfarm sector, annual average MFP growth rates exceeded the long-term (1910–2007) average for the 1910s through the 1940s and in the 1960s, and they have been below the long-term average from the 1970s on. Farm productivity followed a similar pattern two decades later, with above-average productivity growth rates for the 1930s through the 1980s. Combining these two elements, and noting the further decline of the farm share of the total economy, helps account for the surge in national MFP growth during the 1920s through the 1960s. Farm productivity growth rates remained high into the 1970s and 1980s, well above their nonfarm sector counterparts, but by then the farm share of the economy had shrunk to just a few percent—too little to be of much consequence in sustaining the national productivity growth rate.[4]

At the start of the twentieth century, agriculture accounted for one-sixth of U.S. GDP, while employing a much larger share of the national labor force—more than one-third. Over the course of the twentieth century, the rest of the economy grew much faster, and agriculture's share of GDP shrank by a factor of 15: from 15 percent in 1900–10 to 1 percent in 2000–07. Agriculture's contribution to GDP grew in real terms, though its share was shrinking. The farm-sector share of the total labor force fell by a factor of 24: from 34 percent in 1900–10 to 1.4 percent in 2000–07. The shrinking of farm labor as a share of the total labor force reflects a decline in the total labor use in agriculture. Total private employment of labor increased fourfold, while employment of labor on farms shrank sixfold.

II. The Radically Changed Realities of U.S Agricultural R&D

The U.S. agricultural R&D landscape has undergone seismic shifts in recent decades. The balance of R&D spending has moved away from agriculture, away from the public sector, and even away from the United States itself. Critically, public investments in agricultural R&D are now on the decline (in both nominal and inflation-adjusted terms), with a dramatic downsizing in the share of that spending directed toward preserving or promoting agricultural productivity gains.[5]

In 1960, the United States accounted for 20 percent of global investments in public agricultural R&D, most of which were carried out by agencies such as the U.S. Department of Agriculture (USDA) and the Land Grant Universities (Pardey and others 2016a, 2016b). Fast-forward to 2015—the latest year of available global data—and the picture is very different. The U.S. share of the global public-sector total has fallen to 8.9 percent, now second to the 14.5 percent (purchasing power parity) share contributed by China. In 1996, China, India, and Brazil—three agriculturally large, middle-income countries—collectively overtook the United States in public agricultural R&D spending, and by 2015, together they spent an estimated $3.16 on public agricultural R&D for every $1.00 invested in U.S. public agricultural R&D.

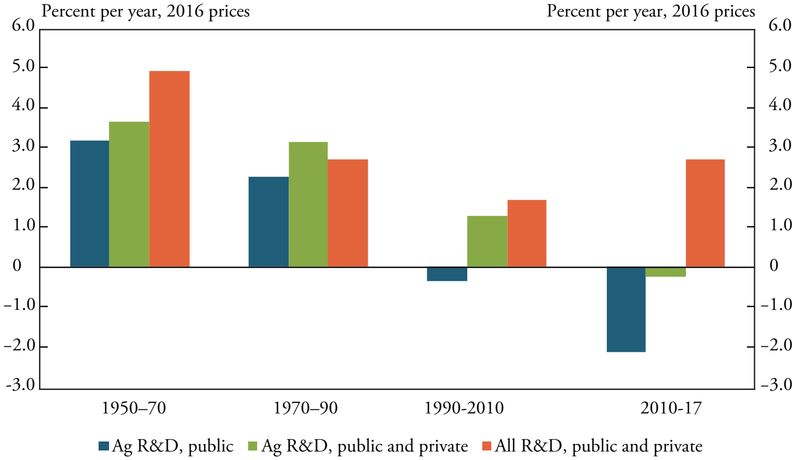
How did this happen? Since at least the middle of the twentieth century, real (inflation-adjusted) spending on U.S. public agricultural R&D grew at an ever-declining rate (Chart 2). Even more critically, starting around 2002, the United States began cutting back, not just slowing down, the rate of growth of spending on public agricultural R&D investments. By 2015, aggregate U.S. spending on agricultural (net of forestry) R&D had retreated to the inflation-adjusted levels that prevailed in 1972. In marked contrast to the U.S. retreat from investments in public agricultural R&D, Brazil, India, and especially China have been ramping up their investments in public agricultural R&D, especially in the decades since 1990.

Chart 3 reveals several other notable features of the changing R&D realities facing U.S. agriculture. First, the growth in private investments in agricultural and food R&D has consistently outpaced the growth in public spending since the 1950s, such that the public share of U.S agricultural and food R&D shrunk from 65.1 percent of the public and private total in 1950 to just 31.3 percent in 2017. Second, like public spending on agricultural and food R&D, private spending on agricultural and food R&D by mainly publicly listed firms has ratcheted down, slipping into negative terms in the past decade. Third, total (public and private) R&D spending for food and agriculture grew at a slower rate than overall R&D spending, thus shrinking the food and agricultural share of total U.S. R&D spending from 3.5 percent in 1950 to 2.3 percent in 2017.

Who foots the public agricultural R&D bill?

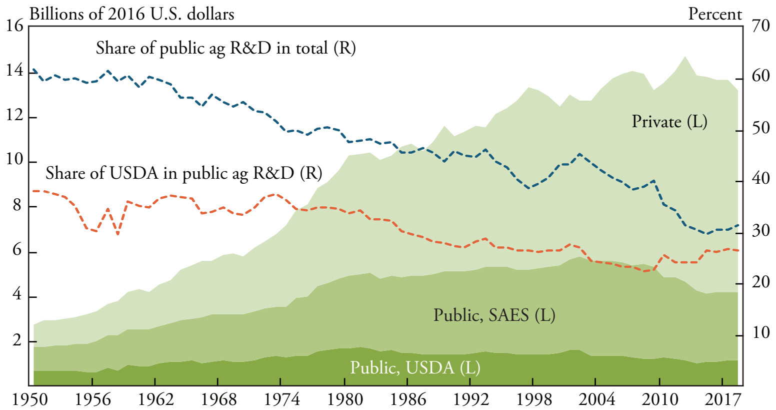
USDA agencies have long relied on federal funding allocated by way of the Farm Bill to carry out research. However, over time, funds from USDA agencies have shrunk as a share of the total pool of public funds directed to agricultural R&D. The State Agricultural Experiment Stations (SAESs)—typically co-located on the campuses of the Land Grant

Chart 2
Whittling Away Investments in U.S. Agricultural R&D, 1950–2017



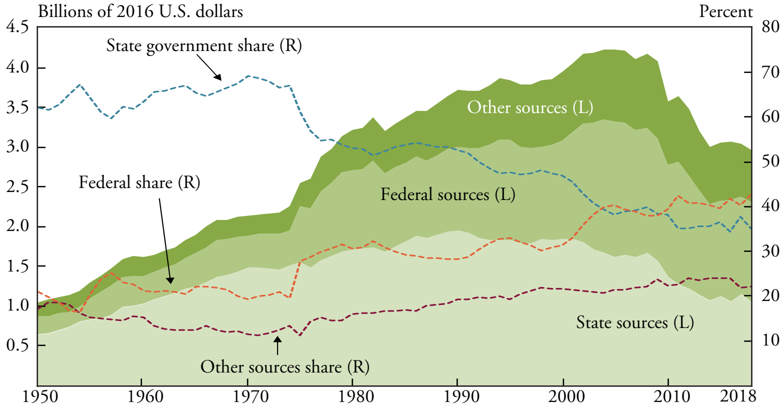
Notes: Public agricultural R&D includes SAES and USDA intramural spending, excluding forestry research. The series were deflated using an agricultural R&D deflator from InSTePP. All growth rates represent averages of annual (year-over-year) rates of the respective periods calculated by the log-difference method. Gross domestic expenditure on R&D (GERD) data begin in 1953, so the growth rate for the first period is for 1953–70.
Sources: Unpublished InSTePP data. The SAES R&D series (excluding forestry) are compiled from unpublished USDA Current Research Information System (CRIS) data files. The USDA intramural series for years prior to 2001 are also from the USDA sources cited in Alston and others (2010, Appendix III) and the National Science Foundation (NSF) thereafter.

Chart 3
Trends in Public and Private Investments in U.S. Agricultural R&D, 1950–2018



Sources: Unpublished InSTePP data. The SAES R&D series (excluding forestry) are compiled from unpublished USDA CRIS data files. The USDA intramural series for years prior to 2001 are also from the USDA sources cited in Alston and others (2010, Appendix III) and the NSF (various years) thereafter.

Chart 4
Shifting SAES Funding Sources, 1950–2018



Sources: Unpublished InSTePP data. The SAES R&D series (excluding forestry) are compiled from unpublished USDA CRIS data files. The USDA intramural series for years prior to 2001 are also from the USDA sources cited in Alston and others (2010, Appendix III) and the NSF (various years) thereafter.

Universities—conduct the majority of U.S. public agricultural R&D: 73.4 percent in 2017, up from 61.4 percent in 1950 (Chart 4).

The sources of financial support for SAES research are more diversified and have changed dramatically over time. The state government share of funding for SAES research fell dramatically; from 69.3 percent in 1970 to just 35.2 percent in 2018 (Chart 4). Federal funding picked up much of the shortfall and now accounts for 42.7 percent of overall SAES funding, more than double its share in 1970. Subtly, but importantly, Farm Bill funding made available to the SAESs by way of the USDA fell markedly as a share of total federal funding to the SAESs over the past several decades: from around three-quarters in the mid-1970s to two-thirds in 2018. The increase in federal funding to the SAESs—from 27.7 percent of total SAES funding in 1975 to 42.7 percent in 2018—stemmed from an increase in mainly competitive, grant-allocated funds coming from agencies such as the National Institutes of Health, National Science Foundation, Department of Energy, Department of Defense, and the U.S. Agency for International Development. Notably, the share of SAES funding from a variety of other sources (including earned income, private sources, and other nonfederal sources) has risen steadily since the 1960s and now constitutes 22.1 percent of total SAES funding.

A reduction in productivity-oriented research

Along with the reduction in state government- and USDA-sourced federal funding, SAES research priorities have also shifted—most notably, to reduce research aimed at preserving or promoting farm productivity. A little over one-half of SAES research spending (53.3 percent) in 2018 was directed to agricultural productivity pursuits, down from the almost two-thirds (64.6 percent) share in 1976. The SAES research agenda has increasingly focused on food safety, food security, and environmental concerns, programs of research that have little if any effect on enhancing or maintaining farm-level productivity. No doubt these other areas of research have social value, but their expansion has been at the expense of, not in addition to, productivity-oriented R&D.

The reduction in emphasis on productivity-oriented R&D has been pervasive throughout the SAES system. In 1976, 37 of the 48 contiguous states directed at least 60 percent of their agricultural R&D spending to productivity-related issues. By 2018, only 10 of those 48 states exceeded the 60 percent productivity threshold, with 14 of them directing less than 45 percent of their agricultural research effort to productivity-related topics.

III. Farm Productivity Drivers

What accounts for the twentieth-century surge and slowdown in U.S. farm productivity? In a recent study, we present a range of evidence related to potential drivers of U.S. farm productivity patterns (Pardey and Alston, forthcoming). We suggest that innovations on farms and the associated structural changes are the proximal causes, while public and private investments in agricultural R&D are a more fundamental source of innovation on farms. We conclude that agricultural R&D spending patterns could account for the more recent slowdown, but not the midcentury surge. We posit that the sluggish adjustment associated with the "farm problem" could account for the mismatched timing between the adoption of innovations and the resulting productivity surge.[6] We find a strong temporal concordance between changes in the structure of farming and patterns of productivity growth.

Agricultural R&D and knowledge stocks

In conventional and widely applied models, current agricultural productivity depends on an agricultural R&D knowledge stock created from investments in agricultural R&D over many years. As described and documented by Alston, Craig, and Pardey (1998), Alston and others (2010, 2011) and Huffman and Evenson (1993, 2006), among others, it takes a long time for agricultural R&D to influence production (the lags in the creation of new knowledge and adoption of technology are long), and then it can affect production for a long time. However, the effective stock of agricultural knowledge becomes obsolete as new technologies embodying new knowledge are developed, or the stock depreciates because of changes in the economic and environmental circumstances in which that knowledge or technology is used—attributable to coevolving pests and diseases and changes in climate or relative prices.

Using widely applied models that link agricultural R&D and productivity, we create measures of knowledge stocks arising from U.S. public agricultural R&D (Alston and others 2010; Huffman and Evenson 2006; Pardey and Alston, forthcoming). We show that these knowledge stocks grew, but at a monotonically declining rate throughout the relevant historical period. This pattern is consistent with the recent slowdown but not with the earlier surge in agricultural productivity, which would have required an R&D funding pattern that caused a commensurate surge in the growth of the stock of knowledge.

Along with the consequences of a decades-prior slowdown in agricultural research investments, a slowdown in agricultural productivity growth might also reflect a change in the effectiveness of those investments. The decline in the productivity share of agricultural R&D, described above, is equivalent to a 20 percent reduction in the effective quantity of productivity-oriented R&D spending for a given total expenditure. Although this is a relevant consideration, most of this shift has been relatively recent and too late to have contributed much to a productivity slowdown beginning a decade or two earlier, once we allow for R&D lags.

A second possibility is decreasing returns to agricultural R&D. It may be increasingly difficult to generate a further proportional gain in productivity on top of past productivity gains for several reasons. First, we may be getting closer to the biological potential of plants and animals (see, for example, Fischer, Byerlee, and Edmeades 2014). Second, we might have to spend a larger share of the research resources maintaining past gains (see, for example, Ruttan 1982). Third, as discussed by Pardey and Alston (forthcoming), some suggest the easy problems have already been solved. However, studies of the rate of return to research investments provide direct evidence contradicting the pessimistic view. Rao, Hurley, and Pardey (2019) report the results from a meta-analysis encompassing 492 studies published since 1958 that collectively reported 3,426 estimates of rates of return to agricultural R&D. They conclude that "the contemporary returns to agricultural R&D investments appear as high as ever" (Rao, Hurley, and Pardey 2019, p. 37). Improvements in the technology of science and in the human capital of scientific researchers have made research more productive, and it seems these gains in research productivity have been sufficient to offset any decline caused by other factors.

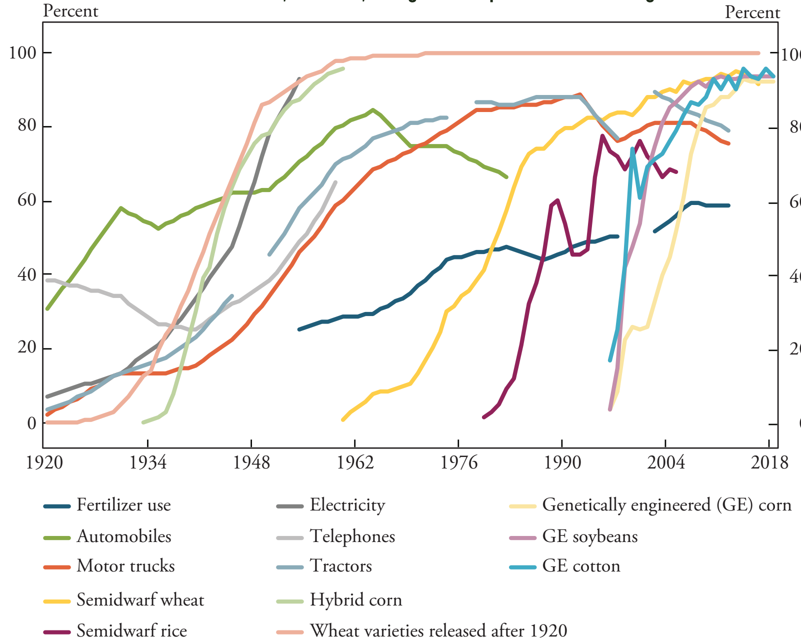
Adoption of farm technologies

One plausible idea is that—like Gordon's (2000) assessment of the "big wave" surge in U.S. MFP—perhaps we could account for the "big wave" surge in the rate of agricultural output and MFP growth in terms of the timing of waves of adoption for several major classes of agricultural innovations (Chart 5). A series of mechanical innovations transformed U.S. agriculture, including tractors, mechanical reapers, combines, and related bulk-handling equipment, which progressively replaced horses and other draught animals and much human labor. These innovations were particularly pronounced in the early decades of the twentieth century. As well as these on-farm changes, farmers benefited from improved technology for long-distance transportation of farm output (including refrigeration and preservation technologies), coupled with investment in roads, railroads, and other public infrastructure (such as those related to rural electrification, telephone service, and irrigation projects).

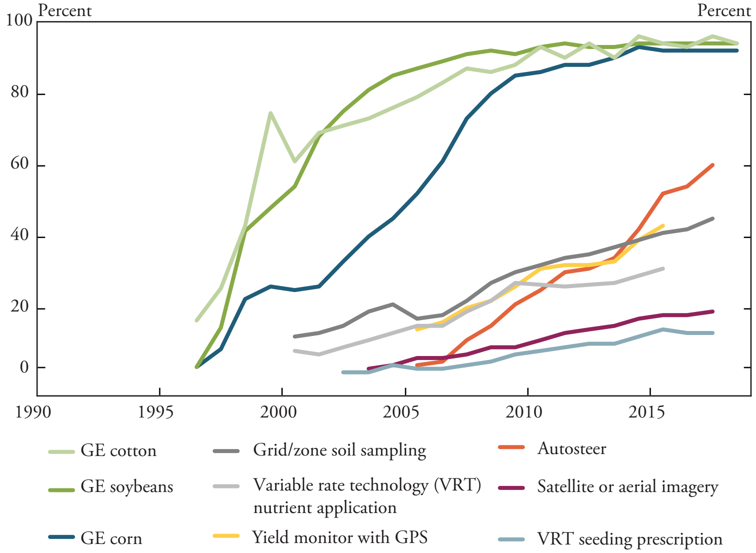
Biological innovations, in particular improved crop varieties that were responsive to chemical fertilizers, took center stage a little later, as illustrated by hybrid corn. In parallel with these genetic changes was the development of modern agricultural chemicals, including various fertilizers, pesticides, herbicides, antibiotics, and hormones, many of

Chart 5
Waves of Adoption of U.S. Farming Innovation, 1920–2018

Panel A: Mechanical, chemical, and genetic improvement technologies



Panel B: Modern genetics and precision agriculture technologies



Note: Adoption rates represent shares of farms or farm area adopting.
Source: Alston and Pardey (2020).

which came after World War II. These were largely private innovations and interlinked with private and public investment in complementary varietal innovations (for example, herbicide-tolerant crop varieties). More recently, much agricultural innovation has emphasized information technologies, including various applications of computer technologies, geographic information systems and related precision production systems, and satellites and various remote- and ground-sensing technologies. Adoption processes for these digital farming technologies are still in their early and slow stages, apart from relatively simple technologies—such as GPS-based remote-sensing and guidance systems—that involve neither large investments in specialized equipment or human capital, nor major changes in farming systems and practices (see Alston and Pardey 2020).

We use data on adoption rates (shares of farmers or farm area adopting) for major examples of each of the categories of innovation to compare the time path of innovation with the time path of MFP (Pardey and Alston, forthcoming). We conclude that the timing of the adoption processes is consistent with our story about a slowdown in the rate of adoption of innovations contributing to a slowdown in productivity, but it does not clearly concord with a surge in the middle tercile of the twentieth century (1940–80). However, the productivity-enhancing consequences of innovation might lag considerably behind the evidence on initial adoption. Just as there is a lag between investing in research and developing technology, there is a lag between the release and initial adoption of technology and its ultimate impact on productivity, with due allowance for the role of adaptation of technology to better match particular contexts. During the in-between time in the middle of the twentieth century, while some farmers had adopted innovations and flourished, many others lagged and fell behind. Those who were slow to adjust and exit agriculture contributed to what became known as the "farm problem."

Structural transformation

The farm problem—excess capacity in agriculture, especially too many farmers—was eventually resolved through consolidation of farms into more economic-sized units, specialized in particular outputs. This consolidation was enabled and promoted by the adoption of innovative technologies, especially labor-saving machines, that enabled considerable economies of size with respect to land and required much less labor to efficiently operate a larger farm area. It took time for the farm sector to absorb these changes and capitalize on the associated efficiencies such that, during the decades following the first introduction of those innovations, American agriculture faced a serious adjustment problem: how to move resources out from agriculture, especially labor, that were earning very low returns in farm production where they were "stuck."

Much of the measured productivity gains, especially in the earlier period, can be attributed to labor-saving innovations that facilitated the consolidation of farms into fewer and larger units. Using newly compiled national- and state-level data on the number and size distribution of farms, we show that much of the agricultural transition took place in the middle of the century, between 1930 and 1970 (Pardey and Alston, forthcoming). This transition was accompanied by an acceleration in farm productivity growth, associated with an acceleration in the rate of farmers exiting the industry, enabling a consolidation of farms into larger operations (see also MacDonald, Hoppe, and Newton 2018 and MacDonald 2020). More recently, the pace of farm consolidation has since returned to what seems to be a more normal, long-term rate commensurate with long-term productivity growth in the economy more generally. Using his measure based on the midpoint of the farm size distribution, applied to U.S. data for 1987–2017, MacDonald (2020) shows that the rate of farm consolidation has been fairly constant over time and across industry sectors for the past 30 years.

Farm size, specialization, and location

As farm size increased, farming also became more specialized. In addition, where that farming occurred also shifted. Both these specialization and spatial movement processes had—and continue to have—considerable consequences for agricultural productivity.

Increasing specialization in U.S. agriculture is evident at both the farm and state levels. Macdonald, Hoppe, and Newton (2018, p. iv) note that, "While few farms specialize in a single crop, field crop operations increasingly grow just 2 or 3 crops, versus 4–6 crops previously. Livestock production continues to shift toward farms that produce no crops, and instead rely on purchased feed." Analyzing state-level specialization trends over the period 1949 to 2006, Alston and others (2010) note that only three states increased the number of agricultural outputs produced, while seven states produced 10 fewer outputs toward the end compared with the beginning of the period. In fact, the majority of the states produced fewer outputs in more recent years, particularly in the Northeast, Pacific, and Mountain regions.

Agriculture involves a large physical footprint, occupying 44 percent of total land area in the United States in 2017. Agricultural production also involves biological processes that make it especially sensitive to the spatial variation in natural or environmental factors (such as soil and sunlight) that are intensively used by the sector. Hence, our measures of productivity can reflect changes in the context in which agricultural production takes place either because of changes in the environment in a given location (changing pests, diseases, or climate, for example) or because of changes in the location of production.

Beddow and Pardey (2015) show that the centroid of U.S. corn crop production moved 279 kilometers north and 342 kilometers west over the period 1879–2007. Changing the location of the crop changes the climate relevant for that crop. In addition, the use of shorter-duration corn varieties (an embodied form of technical change) not only enabled this spatial movement, but also gave farmers greater flexibility in their planting date decisions at any given location. Using phenological measures of climate (specifically temperature and soil moisture) that reflect changes in both the location and timing of corn production throughout the twentieth century, Beddow, Pardey, and Hurley (2014) show that the sensitivity of corn yields to unfavorable weather has declined over time. In this instance, embodied and unembodied technological changes have muted the detrimental productivity consequences of the variability of weather over time.

Physical and regulatory environments

Environmental factors could have contributed to the surge and slowdown in measured productivity growth. In terms of the physical environment, climate change, invasive pests and diseases, evolving pesticide resistance, and declining natural resource stocks could all have contributed to a more challenging physical and economic environment for agricultural production, adding to the demands for maintenance research just to keep yields from falling and costs from rising.[7] In addition, the economic environment for producers—including regulations governing production practices on farms—has become more difficult in some ways that may help account for the observed productivity patterns. The story reflects both environmental externalities that are not reflected in our MFP measures and the effects of policies that address those externalities.

Pesticides illustrate the main ideas here. The surge of farm productivity growth immediately following World War II was associated with a surge in the use of agricultural chemicals, especially synthetic fertilizers and pesticides (Pardey and Alston, forthcoming). Conventional measures of productivity growth do not account for the negative externalities associated with these agricultural chemicals, and in this sense, our measures overstate the true gains in productivity. The past 50 years have seen increasing public concern over the environmental consequences of agricultural pesticide use and greater environmental regulation of agricultural production. Many pesticides have been banned. A direct consequence of these regulations has been to reduce agricultural productivity—both measured and actual. Similar thinking applies to the development of intensive livestock production systems and the progressive, increasingly stringent regulation of the use of antibiotics, hormones, and other veterinary medicines, and the regulation of other production practices. Together, these aspects might have contributed both to the measured surge (reflecting unmeasured externalities or unmeasured consumption of poorly priced natural resource stocks that contributed to overestimated productivity growth) and to the subsequent slowdown (reflecting the consequences of regulations that internalized some of those costs). It is not easy to guess at the empirical importance of these aspects, but they are surely part of the story.

IV. Looking Forward

In the current agricultural environment, demands for private investments in innovation are being influenced by government through the prospect of new regulations (or taxes) applied to agricultural production—including technological regulations and environmental regulations to reduce greenhouse gas emissions and other spillovers from agriculture—and through the influence of policy on the supply of farming inputs (especially labor and water) and on the markets for farm products.

This paper documents a significant downsizing of public support for agricultural R&D and a major decline in the share of that research devoted to preserving or promoting productivity growth. This shift in support for public sector R&D (in terms of both total investment and the balance of investments) reflects a changing role of scientific evidence in policy and shifting public preferences (Alston, forthcoming). Agricultural R&D investments are being scaled down even though meta-evidence shows that past U.S. investments in R&D have yielded very favorable returns: median reported benefit-cost ratios are in the range of 8:1. Sustained U.S. investment and innovation will be required to preserve past productivity gains in the face of climate change, coevolving pests and diseases, and changing technological regulations—let alone increase productivity. Great potential exists for innovation in crop and livestock genetics and digital farming technologies to generate new products and production processes, but innovators have to overcome increasingly strong headwinds from social and political forces that seek to dictate technology choices.

Endnotes

[1]The year 2007 is the latest year in our consistent series of data on input, output, and productivity.

[2]More complete descriptions of the ideas and information summarized in this paper can be found in Alston and Pardey (2020), Pardey and others (2016a, 2016b), and Pardey and Alston (forthcoming).

[3]As Pardey and Alston (forthcoming) show, national MFP growth is equal to the sector-input-share weighted average of farm and nonfarm MFP growth.

[4]Pardey and Alston (forthcoming) confirm these informal impressions by fitting a cubic polynomial trend model in logarithms to each of the MFP data series summarized in Table 1 for the period 1910–2007. In each case, the model fits the data fairly well (R^2 values of at least 0.98), and we can strongly reject the nested special case of a linear model with a constant exponential growth rate against the alternative of a cubic model that implies a surge and a slowdown.

[5]Throughout this paper, unless we state otherwise, "agricultural R&D" refers to the aggregate of R&D related to food and agriculture.

[6]Sumner, Alston, and Glauber (2010) provide a concise review and cite several notable economists who have written on the issue, including Houthakker (1967, p. 5) who wrote, "The Farm Problem, it will be argued here, is primarily a problem of economic growth. To put it briefly: … economic growth requires a steady shift of labor and other resources from agriculture to other sectors. Since there is resistance to this shift, there are usually too many people in farming and as a result per capita farm income is depressed." See also Gardner (1992, 2002).

[7]Many expect the variation in climate (or pest and disease) pressures to pick up pace and increase in the decades ahead, implying an increase in demand for maintenance research.

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Interacting with the Next Wave of Farm Operators: Digital Agriculture and Potential Financial Implications

By Terry W. Griffin, LaVona S. Traywick, and Elizabeth A. Yeager

Digital agriculture and the utilization of technology on the farm has garnered increased attention in recent years. Farmers, lenders, advisors, and researchers frequently ask whether additional technology can increase productivity and the resulting profitability of the farm operation, and lenders and marketers ask whether they should focus on the demographics of their customers differently—considering, for example, how different generations respond to or adopt new technology. This paper looks at the adoption of various precision agriculture technologies by Kansas farms and breaks the adoption down by sole proprietor and multiple-operator farms. We find that adoption indeed varies across generations as well as by generation mix for multiple-generation farms. We also predict that the current younger generation will control the majority of farm operations at an older age than previous generations.

The economics of digital agriculture have been evaluated since the advent of global navigation satellite systems (GNSS), but the consensus has been that the economics are site-specific—analogous to a high-tech version of "it depends" (Griffin and others 2004; Lowenberg-DeBoer and Swinton 2015). The profitability of precision agriculture, including reduced input usage, has been reported at the national level based on

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data from the U.S. Department of Agriculture (USDA) Agricultural Resource Management Survey (Schimmelpfennig and Ebel 2016; Schimmelpfennig and Lowenberg-DeBoer 2020; Schimmelpfennig 2016, 2018). In their study of farmers' adoption of precision agriculture technologies, Ofori, Griffin, and Yeager (2020) report that the farm debt-to-asset ratio was an important factor in predicting farms' adoption of technology, and that younger, more profitable farmers were more likely to make capital investments for digital agricultural technologies. Generation, or birth year, of farm operators was also important in describing the adoption path of technology, emphasizing that younger farmers tend to favor technology. Younger operators were also more likely to embrace farm data, such as yield monitor data and soil maps, as an intangible resource (Ofori, Griffin, and Yeager 2020).

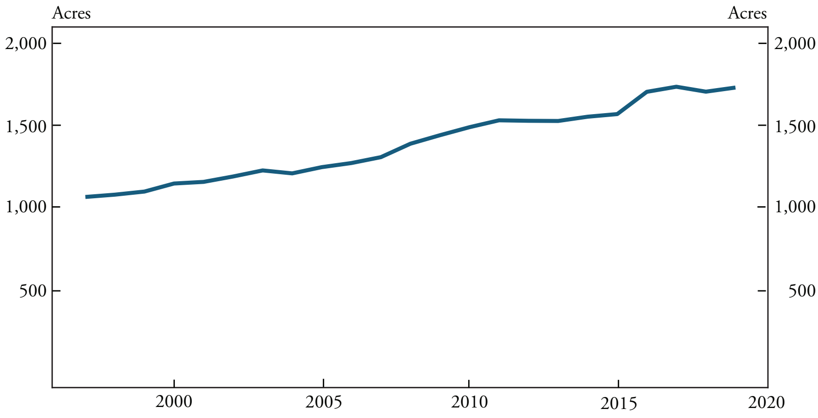
Numerous studies have shown that the utilization of precision agriculture technology can increase productivity and profitability. The presence of yield maps and soil maps has been shown to increase technical efficiency marginal effects by 1.1 to 7.2 percent and 0.4 to 2.3 percent, respectively (McFadden 2017). Yield monitors with variable rate technology have been associated with a 4 percent reduction in fertilizer costs (Schimmelpfennig 2018). Farms fully utilizing automated guidance could increase farm size from 3,000 to 3,335 acres using the same equipment and still complete field operations in a timely manner, thus reducing fixed per-acre equipment expenses (Griffin, Lowenberg-DeBoer, and Lambert 2005). Adopters of soil testing with variable rate application had 33 percent higher nitrogen productivity than non-adopters on below-average soils (Khanna 2001). It is generally expected that data-endowed farmland will command higher rental rates once the "Big Data" system in agriculture is operational (Griffin and others 2016). Researchers predict similar relationships for farmland with adequate wireless broadband connectivity.

The profitability of farm data has been relatively more elusive to quantify than the digital technology generating that farm data (Coble and others 2018). Network externalities (the demand for a good or service being a function of the number of users of that good or service) complicate the valuation of farm data, especially when considering perspectives of only one agent—for example, farmer, data platform, or society (Griffin and others 2016). Farm data valuation is further complicated by ownership, access, and permissions to control, share, and access data arising from digital agriculture technologies (Ellixson and others 2019). Although a market for farm data has yet to develop, utilization of farm data by the agricultural industry is not likely to be a temporary phenomenon but an enduring segment of how farmers interact with suppliers, customers, and peers (Griffin and others 2016; Ferrell and Griffin 2018). The complexities of farm data valuation isolated for use by the farmer within the farm gate, as opposed to within an aggregated community for use by other agents in the agricultural community, remain a problem to be solved (Ferrell and Griffin 2018). Similar to digital technology, farm data favor larger-acreage farms that can spread out associated fixed costs.

Long-term trends indicate that the consolidation of farm acreage will likely continue, and the additional acreage requires farmers to either devote more labor hours, or human capital, to working the land or adopt technologies to decrease the workload. Decades of evidence suggest nearly constant acreages of farmland are being managed by fewer operators each year (MacDonald and others 2018). Average acreage on midwestern Corn Belt farms was relatively stable until the 1950s, when consolidation began to occur presumably in conjunction with the mechanization of row crop agriculture (Hart 2003). The total number of farm operations in the United States fell from nearly 7 million in 1940 to 2 million in 1980 (MacDonald and others 2018). Farm consolidation has been documented with each USDA Census of Agriculture since 1982. Lin and others (1980) forecast that the consolidation of farms and acreage being controlled by fewer farm operators would continue for the foreseeable future. Over the last 20 years, average crop acreage on Kansas farms has steadily increased from 1,100 acres to over 1,700 acres (Chart 1).

The adoption of labor-saving technologies has contributed to consolidation (MacDonald and others 2018). Digital agricultural technology may not only favor larger-acreage farms due to the fixed costs of adoption but may be most beneficial for farm operators prepared to add new tracts of farmland to their existing acreage (Hart 2003). Skilled operators willing to devote human capital are more likely to expand their operations by utilizing technology (Langemeier and Shockley 2019).

Chart 1
Average Crop Acreage of Kansas Farm Management Association Member Farms



Source: Kansas Farm Management Association.

Full utilization of digital agricultural technologies and farm data are not simply a matter of farm-level adoption decisions. One leading barrier to realizing the benefits of digital agriculture is the lack of sufficient wireless broadband connectivity, especially in regions where agricultural commodities are produced (Whitacre, Mark, and Griffin 2014). In addition to the policy implications for connecting rural schools, hospitals, libraries, and residences, substantial market pressures exist for farm equipment to be wirelessly connected via the "internet of things" (Köksal and Tekinerdogan 2019). Farmland without adequate wireless connectivity may suffer lower land values and rental rates due to operators not being able to fully enjoy telematics capabilities.

In addition to highlighting that the economics of digital agriculture are site-specific, the proportion of cohort farms' acreage and local wireless connectivity are important determinants used in farm data valuation. Wirelessly connecting to mobile devices empowers farm operators to take more control of digital agriculture and participate in networks of farm-data utilization. Although the aforementioned digital technologies were developed before the advent of modern smartphones, connected devices have increasingly facilitated digital agriculture within and beyond the farm gate due to ever-increasing capabilities and flexibility. The United Soybean Board (2019) reports that nine in 10 farm operators use smartphones. At the American Farm Bureau Federation's 2020 Annual Convention, 86.5 percent of participants reported connected technologies with applications (mobile apps) as essential. By 2018, 70 percent of farmers had downloaded agricultural apps to their smartphones (Farm Journal 2018). The Purdue/CropLife survey of agricultural service providers reports the increased prevalence of telematic utilization by service provider, from a low of 7 percent in 2011 to 37 percent by 2020 (Erickson and Lowenberg-DeBoer 2020). How will the agricultural industry interact with, market to, and service wirelessly connected farm operators in the next generation? To contribute to this discussion, we evaluate the demographics of Kansas farmers with respect to their technology adoption.

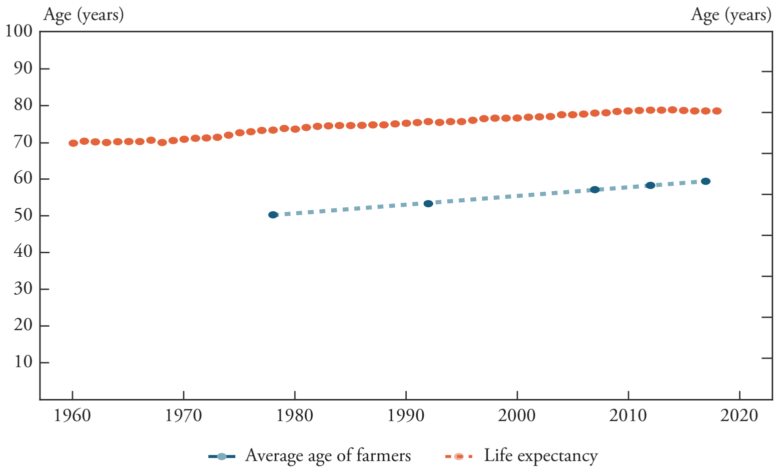
I. Farm Demographic Data and Analysis

Information on farmers' age and experience has long been of interest to the agricultural community. The USDA National Agricultural Statistics Service (NASS) Census of Agriculture reports the average age of farmers every five years. The most recent nationwide statistics report the average age of farmers as 57.5 in 2017, up by 1.2 years from 2012 (USDA 2019). The average age of farmers reported by NASS has consistently increased at similar rates for several decades (Chart 2). The annual increase in average age of farmers reasonably parallels life expectancy.

With respect to technology adoption and utilization, the age and experience (measured in number of years farming) of farm operators have been the focus of marketing efforts by manufacturers and educational programming by the Land Grant University System. Data from the Kansas Farm Management Association (KFMA) were analyzed to provide detailed insights into age and experience as related to digital agriculture technology adoption. The KFMA maintains databases of financial, production, and technology data for farmer members in Kansas. The KFMA data provide the opportunity for detailed analyses of age and experience as related to the adoption of digital agriculture technology. Since 2015, KFMA economists have collected and annually updated technology utilization (Ofori, Griffin, and Yeager 2020).

Chart 2

Life Expectancy for General U.S. Population versus Average Age of Farmers



Sources: World Bank and USDA Census of Agriculture.

Current farm operator demographics and summary statistics of technology adoption

We applied generational attributes as defined by the Pew Research Service to the KFMA data (Dimock 2019). Birth year ranges and proportion of KFMA farms in single-operator sole proprietorship and multiple-operator farms are presented in Table 1. The generational proportions were similar for sole proprietors and multiple-operator farms. Nearly half of farmers on multiple-operator farms and sole proprietors were Baby Boomers (48.5 percent and 51.2 percent, respectively). In 2018, Millennials were 11.8 percent of multiple operators and 9.8 percent of sole proprietors. The Silent Generation and Generation X were similar to each other at 18 to 21 percent for both categories.

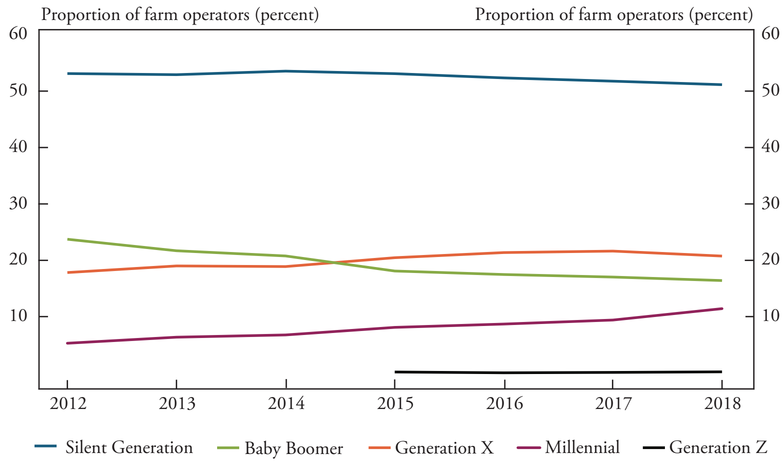
Assuming the linear trend lines presented in Chart 3 persist into the future, Silent Generation operators will have exited management of farms by 2029, when their youngest member will be 84 years old. One-third of farm operators are expected to be Millennials by 2041, when these operators will be 45 to 60 years old. As farm operators age, the agricultural industry must learn to market products and services to middle-age Millennials and Generation Z rather than Baby Boomers and Generation X (Griffin and Traywick, forthcoming).

Table 1
Kansas Farm Operators across Generations in 2018

Generation	Birth year	Multiple operators (percent)	Single operator (percent)
Silent Generation	Before 1945	18.2	20.4
Baby Boomer	1946–64	48.5	51.2
Generation X	1965–80	21.2	18.3
Millennial	1981–96	11.8	9.8

Source: Kansas Farm Management Association.

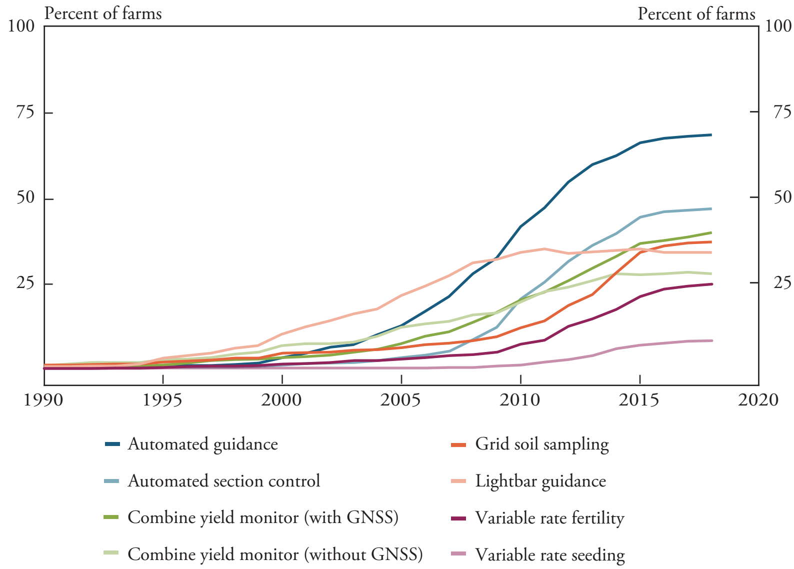
Chart 3
Proportion of Kansas Farm Operators by Generation



Source: Griffin and others (2019).

By January 2019, 84 percent of KFMA farmer members reported having used at least one of eight precision technologies, while the remainder reported having "never used" any technology. The eight technologies evaluated included GNSS-equipped yield monitors, yield monitors without GNSS, variable rate fertility, variable rate seeding, precision soil sampling, lightbar, automated guidance, and automated section control. Chart 4 shows the percentage of KFMA farms adopting each technology by year.

Chart 4
Percent of Farms with Agricultural Technology



Source: Griffin and Yeager (2019).

Defining innovators and early adopters among Kansas farm operators

We assessed characteristics of farms at different points along the adoption path, placing assumptions on the shape of expected adoption curves; specifically, we evaluated the age and experience for "innovators," "early adopters," and "early majority" (Rogers 2003). Rogers (2003) defines diffusion of innovations by percent adopted. "Innovators" are the first 2.5 percent, "early adopters" are the next 13.5 percent, and "early majority" the next 34 percent. This study reports age and experience demographics for each agricultural technology for these categories.

Age and experience of technology adopters were calculated for 2018 based on birth year and the year they commenced farming. The average age of adopters was 59.6, substantially younger than 62.7, the average age of non-adopters. The average age of technology adopters and non-adopters in Kansas was higher than the 57.5-year-old average age of all farmers reported by the USDA NASS Census of Agriculture. The average experience of non-adopters in 2018 was 39.7 years, 2.6 years longer than adopters. Tables 2 and 3 show the distribution of technology

Table 2
Average Age of Innovation Group by Technology

Technology	Innovators	Early adopters	Early majority
Automated guidance	49.2	47.5	51.9
Automated section control	47.0	48.6	–
Yield mapping	45.8	47.0	–
Yield monitor	40.0	49.5	–
Grid soil sampling	47.5	52.0	–
Lightbar	45.0	44.9	–
Variable rate fertility	49.9	51.9	–
Variable rate seeding	53.8	58.3	–

Source: Kansas Farm Management Association.

Table 3
Average Farm Experience of Innovation Group by Technology

Technology	Innovators	Early adopters	Early majority
Automated guidance	27.2	25.3	29.3
Automated section control	24.5	26.1	–
Yield mapping	20.9	24.2	–
Yield monitor	18.1	27.1	–
Grid soil sampling	22.7	30.3	–
Lightbar	20.0	22.6	–
Variable rate fertility	25.4	30.6	–
Variable rate seeding	31.2	36.5	–

Source: Kansas Farm Management Association.

adoption status by age and experience, respectively. Although differences exist, similar patterns were observed for both age and experience.

Our tests indicated that age and experience were statistically different from adopters to non-adopters. The null hypotheses that age or experience of adopters were no different from non-adopters were rejected at any conventional significance level when all technologies were evaluated together. We conducted multiple means comparisons to evaluate if average age and experience differed across technologies.

Technology by average age and adoption status

We evaluated the average age of adopters and non-adopters of technology, finding that the average age of adopters was younger than non-adopters for all eight technologies. This supports the finding from other studies that younger generations are more willing to adopt new technology. We compared the age of adopters pairwise across all technologies. Adopters of lightbar were statistically older than adopters of automated guidance, automated section control, grid soil sampling variable rate fertility, and variable rate seeding. The age of adopters of automated guidance only differed for lightbar. Adopters of variable rate seeding were statistically different from adopters of yield monitor with GNSS, yield monitor without GNSS, and lightbar.

Using innovation categories suggested by Rogers (2003), we evaluated the average age and experience of farms for innovators, early adopters, and early majority (where possible). Innovators and early adopters were assessed for all eight technologies. The most readily adopted technology in 2018, automated guidance, is currently being adopted by the late majority. Descriptive statistics for innovators, early adopters, and early majority are provided for all eight technologies.

Automated guidance was the only technology with more than 50 percent of farms adopting, achieving innovator status by 2000, early-adopter status by 2006, and early-majority status in 2012. Automated section control met innovator and early-adopter status in 2005 and 2009, respectively. Combines equipped with GNSS-enabled yield monitors met innovator status by 1997 and early-adopter status by 2009 (Table 4).

Information-intensive technologies took longer to go from innovator to early-adopter status than embodied-knowledge technologies (Griffin and others 2004). The three information-intensive technologies took longer to achieve early-adopter status than the other five technologies. The three embodied-knowledge technologies achieved early-adopter status relatively quickly.

Age and farming experience characteristics of technology adopters

Based on the year that status was achieved, we determined the average age for each innovation phase for all eight digital agricultural technologies. The average age of innovators and early adopters of variable

Table 4
Year Innovation Status Achieved Relative to Commercialization Date by Technology

Technology	Date available	Innovator (2.5 percent)	Early adopter (16 percent)	Early majority (50 percent)
Automated guidance	2000	2000	2006	2011
Automated section control	2004	2004	2009	–
Yield mapping	1994	1997	2009	–
Yield monitor	1992	1995	2009	–
Grid soil sampling	1994	1997	2011	–
Lightbar	1995	1995	2003	–
Variable rate fertility	1996	2003	2013	–
Variable rate seeding	2006	2008	2018	–

Note: As of 2018, automated guidance was the only technology to surpass a 50 percent adoption rate.
Source: Kansas Farm Management Association.

rate fertility was 49.9 and 51.9, respectively. Innovators were consistently younger than early adopters across all eight technologies (Table 2).

Innovators were generally less experienced than early adopters across the agricultural technologies evaluated. Innovators of seven of the eight technologies were younger than the early adopters. The exception was automated guidance. The experience for adopters of automated guidance was nearly the same for innovators and early adopters at 27.2 and 25.3, respectively. However, it should be noted that the innovators averaged more than 20 years of experience, such that they were not considered inexperienced (Table 3).

Automated guidance reached early majority in 2011, when 50 percent of Kansas farms adopted the technology (Table 4). The early majority averaged 51.9 years old, ranging from 20 to 82 years old (standard deviation of 12.2) (Table 2). Operators meeting early majority status for automated guidance had 29.3 years of experience ranging from zero to 63 years (standard deviation of 13.5) (Table 3).

II. Farm Data Valuation

The utilization of digital technologies has generated a large volume of site-specific data. Spatial data analysis requires specialized skills and human capital investment, so it is not a core competency of most agriculturalists. One solution to this problem has been the development of a potential market for farm data analytics. Analysis is often provided in the form of field-level prescriptions, yield and variable rate mapping, or farm management recommendations collectively referred to as "Small Data."

Small Data within the farm gates

Little is known about the marginal benefits and costs that accrue to the economic agents (farmers, retailers, analytics platforms, or manufacturers of crop protection chemicals, seed, and equipment) for participating. The theory of economic networks suggests, however, that as more farms provide data in such a market, the analysis offered by the community analytics platform, or "Big Data," becomes more valuable to each individual farmer. Uncertainty exists regarding the number of farmers and data platforms providing analytics participating in the market. Currently, there are a large number of platforms offering services and vying for farmers to contribute data, with no firm prevailing over others, and a relatively small share of farms participating in the market.

Participation in digital services provides benefits for farm management, especially agricultural lenders. Secondary benefits exist with automated tracking of input application, specifically automatically populated financial statements built from connecting to planning tools provided by farm management information systems. When seed or fertilizer are purchased and applied with automated controllers such as variable rate, as-applied maps are created that provide details that populate enterprise budgets, but with detail sufficient to create a budget for every acre on the farm. The cost half of cash flow statements could easily be updated in real time as rates and prices change and with electronic permissions set to be shared with agricultural lenders.

Big Data beyond the farm gates

An analysis of data from a single farm commingled with data from thousands of farms can provide benefits for every participant. This "beyond the farm gate" data analysis has been referred to as "Big Data" (Coble and others 2018). If data service analyzes observational planter and yield monitor data from thousands of farms coupled with information about the management practices of those farms, "G × E × M" (genetics × environment × management) analysis could be conducted to determine how factors work together to influence crop performance (Ferrell and Griffin 2018). The resulting information could help consultants provide better insights and recommendations to their farmer clients about how to optimize their operations. Scouting and soil sample data collected across geographic regions could provide important information about the potential for nutrient runoff to pollute nearby water bodies or provide advance warnings of pest or disease outbreaks that could prevent many farms from experiencing any productivity loss at all. Analyzing the data of many farms can create products that provide value to individual farms and also provide value to a "community" of data-sharing farms.

Data aggregators and analysts will likely command a share of that value and may create value completely separate from that of the farm operator. With enough data, analysts may be able to provide agricultural retailers with an abundance of asymmetric information to allow targeted laser marketing efforts to the farmer. Although this might benefit some farmers by helping identify products that are a best fit for their operation, asymmetry may lead to pricing practices that are disadvantageous to the farmer. Knowledge of how bundles of products perform in a specific region empowers manufacturers and retailers to improve supply chain management and lower their costs. With enough information from aggregated data, aggregators and analysts may derive insights important to commodity markets before government reporting agencies and obtain an advantage in commodities trading.

III. Future Farm Operators

The age and length of farm experience continues to be associated with technology adoption. Younger, less experienced farm operators tend to adopt technology more readily than their older, more experienced counterparts. In fact, these characteristics are such strong indicators of predicted adoption that manufacturers may use this information to target specific individuals. Educational programming on the returns of adopting individual technologies may be aimed at specific age groups.

In our sample, multiple-operator farms tended to adopt more technology than sole-proprietor farms. For single-operator farms, Millennials adopted less technology than Baby Boomer or Generation X, most likely due to less financial ability (Table 5). Millennials on multiple-operator farms adopted much more technology than Millennials on sole-proprietor farms (Table 6). Having a Baby Boomer or Generation X on multiple-operator farms providing financial stability may explain the influence Millennials had on investment decisions. The Millennials on multiple-operator farms may have also received additional education, training, or knowledge of digital agriculture technologies before joining the farm operation.

Even though the most recently available agriculture technology has been utilized for 14 years, the low percentage of farmer usage could be because not all current farmers are likely candidates for agriculture technology (Ofori, Griffin, and Yeager 2020). In general terms, Baby Boomers' technology lags behind that of younger generations for multiple reasons. Baby Boomers are less accustomed to technology than younger cohorts, and remaining current with new technology requires human capital expenditures, so they tend to be late adopters (Kamin, Lang, and Beyer 2017; Van Volkom, Stapley, and Malter 2013; Shen 2020). Although it is unlikely that Baby Boomers, the generation currently comprising the majority of farm operators, will ever adopt a complete bundle of technologies without the influence of younger operators, nearly all acreage is expected to be managed with some sort of precision technology after a sufficient number of farm consolidations occur. In the future, technologies such as variable rate fertilizer application are likely to be ubiquitous, especially if site-specific decisions are passed to the operator.

Less discussed is the mental capacity needed for adaptation to technology. Adopting technology necessitates sensory, cognitive, and motor resource investment, and physiological or cognitive decline, more than age itself, has been shown to determine rates of adoption of technology (Lindenberger and others 2008; Shen 2020). The physiological declines associated with aging could be offset by aging farm operators adopting labor-saving technologies, such as automated guidance; however, the cognitive decline associated with aging would lend itself to not adopting data-intensive technology such as variable rate technology (Feder, Just,

Table 5
Proportion of Single-Operator Farms with Technology by Generation

Technology	Silent	Baby Boomer	Generation X	Millennial
Yield mapping	4.7	14.0	16.3	8.8
Yield monitor	8.1	14.8	15.5	7.5
Automated guidance	12.8	24.2	24.4	13.1
Automated section control	7.4	16.1	18.7	10.0
Lightbar	10.8	22.2	18.7	10.0
Grid soil sampling	7.1	14.1	13.8	7.5
Variable rate fertility	2.0	9.1	9.9	6.2
Variable rate seeding	1.4	5.5	5.7	1.9

Note: As of 2018, automated guidance was the only technology to surpass a 50 percent adoption rate.
Source: Kansas Farm Management Association.

Table 6
Proportion of Operators from Multiple-Operator Farms with Technology by Generation

Technology	Silent	Baby Boomer	Generation X	Millennial
Yield mapping	14.7	36.2	26.9	14.9
Yield monitor	25.3	38.3	25.7	12.8
Automated guidance	40.0	62.8	40.4	22.3
Automated section control	23.2	41.7	31.0	17.0
Lightbar	33.7	57.6	31.0	17.0
Grid soil sampling	22.1	36.6	22.8	12.8
Variable rate fertility	6.3	23.4	16.4	10.6
Variable rate seeding	4.2	14.1	9.4	3.2

Source: Kansas Farm Management Association.

and Zilberman 1985). The perceived ease of use, or learning curve, of the technology must be weighed with the perceived usefulness or benefits. If the learning curve seems too steep, it may hinder technology adoption for older farmers, especially before these technologies become sufficiently passive to the user or equipment operator.

Older farmers may not be able to devote necessary human capital or may be unwilling to accept the profitability risks of unproven technology. However, one subset of farm operators who are likely to adopt technology include those belonging to the younger, experienced, more educated, higher-farm-acreage demographic. Farm operators with these characteristics are generally Millennials or members of Generation Z.

Millennials, in general, are technologically savvy, readily look for new technological advances, value their family time, lack job loyalty, and are environmentally and socially conscious (Barroso and others 2020; Howe and others 2000; Suh and Hargis 2016). Millennials may see agricultural technology as less intimidating than their older counterparts, a way to protect the environment by preventing fertilizer overuse and possible runoff, and time-saving—providing more family time.

Future technologies are expected to reduce the reliance on human capital necessary to make technology work. These expectations are especially true for Generation Z, who value cutting-edge products over industry status quo. If the product or service does not perform as anticipated, farm operators of Generation Z are expected to move on to the next technology (Johnson and Sveen 2020). Another insight that the agricultural industry must anticipate is how future generations may express loyalty differently than previous generations. Commodity produced, education level, and age have been associated with farmers' perceived brand loyalty (Harbor, Martin, and Akridge 2008). Millennials already in the workforce tend to change jobs every few years and do not hold the same brand loyalty as members of the Silent and Baby Boomer generations (Suh and Hargis 2016).

A counterargument to the generational divide is how people of a certain age behave similarly to previous generations at that same age. Although Millennial and Generation Z farm operators are younger, with greater interest in technology, at some point in the future they may behave similarly to how operators born in the Baby Boomer generation behave (Pitt-Catsouphes and others 2012). However, Millennials and members of Generation Z were born during an era with the internet, which has influenced their thought processes, trust, and risk aversion levels.

Discerning farm operators (Millennials and Generation Z) who place less value on loyalty than previous generations are unlikely to readily trust site-specific prescription recommendations from retailers profiting from increased sales of inputs (Gurau 2012). Members of Generation Z have already differentiated themselves from

Millennials with respect to media preferences; they are known to actively block advertisements. Separation of input sales (fertilizer, for example) from custom applications and site-specific prescription recommendations may be necessary before younger farm operators trust variable rate technology services.

As a whole, members of Generation Z are also technologically savvy, as they have grown up with smartphones and other gaming devices, but they also seek financial value in their choices, are interested in finding practical ways to complete tasks well, and desire individualizing experiences for themselves (Johnson and Sveen 2020). With these characteristics, it is possible that they will accept agriculture technology for its potential financial value, its practicality, and its ability to allow the farm operator to maximize individualization to specific needs. Variable rate fertilization is a prime example of individualization, where fertilizer is applied only where needed and not across the whole field. The same need for individualization may be seen when purchasing other forms of farm technology. It is predicted that Generation Z operators will not be content with technologies that come standard as original equipment, but will desire to customize which technologies they use and to what extent.

Moving forward, manufacturers of agriculture technology must consider how Millennials and Generation Z behave with respect to technology adoption rather than expecting similar adoption paths as the Silent and Baby Boomer generations. While there is scarce literature on the family farm inheritance skipping generations, there are many business and tax reasons for transferring farm ownership to the grandchild instead of the child. Unlike other family-owned businesses, with farming, much of the wealth is in equity, not cash, and the physical demands and long hours are very different from traditional desk jobs. Thus, skipping a generation for farm inheritance may include the factor of age along with financial factors. The average age of farmers is increasing at a higher rate than the life expectancy in the United States (Chart 2). While the average retirement age in the United States is 62, 49 percent of Kansas farm operators are beyond retirement age, and 69 percent of all non-operator agricultural landlords are age 65 or older (Mather, Jacobsen, and Pollard 2015; Bigelow, Borchers, and Hubbs 2016). It makes sense to turn farm operations over to a grandchild in midlife rather than a child at retirement age when the farmer finally retires. With this foreseeable trend ahead, the decision makers of tomorrow may not follow a traditional pathway through the generations.

IV. Conclusions and Future Research

The generational cohort farmers belong to may have more influence on their adoption of farm technologies than many other factors previously studied. When looking at the profitability of technologies, the farmer considers more than just financial gain; human capital, social ties, and environmental stewardship all play a role in adoption rates. To market farm technologies successfully, the age or generation of the farmer—more than the crop—should inform the advertising message.

We find that the adoption of precision agriculture has varied across generations as well as by generational mix for multiple-generation farms. While discussions of operator age, experience, and technology adoption are of interest on their own, policymakers are likely to consider generational attributes of current farm operators and those who will be making the majority of farm decisions in five or 10 years, as well as how farm data, or Big Data, influences decisions within the farm gate and in a community of aggregated agricultural data. Agricultural lenders are leaning more on insights provided by farm data in addition to general customer attributes to reduce loan risks.

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An Empirical Investigation of Productivity Spillovers along the Agricultural Supply Chain

Sergio H. Lence and Alejandro Plastina

Total factor productivity (TFP) has long been recognized as a major engine of growth for U.S. agriculture in the post-war period, despite the methodological differences in the approaches used to calculate it.[1] Furthermore, TFP growth in the farm sector compares very favorably to similar measures of productivity growth in other sectors of the U.S. economy (Kendrick and Grossman 1980; Jorgenson, Gollop, and Fraumeni 1987; Jorgenson and Schreyer 2013; Jorgenson, Ho, and Samuels 2014; Garner and others 2019). In particular, Jorgenson, Ho, and Samuels (2014) find that although the farm sector ranked 15th out of 65 industries in its contribution to national value-added from 1947 to 2010, it ranked fifth in its contribution to national productivity growth, accounting for 7.5 percent of total U.S. TFP growth over the same period. Using a different data set, Garner and others (2019) find that the farm sector ranked fourth in TFP growth across 63 industries in the United States from 1987 to 2016.[2]

Prior agricultural economics research has contributed to policy discussions on how to increase food, fiber, and, more recently, biofuel output using fewer inputs mostly by identifying endogenous drivers of agricultural productivity—and, to a lesser extent, by decomposing TFP changes into more meaningful economic terms that can be addressed

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through alternative policy instruments.[3] Agricultural economics researchers have extensively evaluated the effects of knowledge spillovers from other sciences into agriculture as well as the effects of knowledge spill-ins from agricultural research and development (R&D) conducted in other jurisdictions on agricultural productivity (Coe and Helpman 1995; Schimmelpfennig and Thirtle 1999; Huffman and others 2002; Alston and others 2010; Plastina and Fulginiti 2011).[4] However, none have yet analyzed productivity spillovers between the agricultural sector and other economic sectors. This issue is important because knowing the ways in which agricultural productivity affects, and is affected by, productivity in other sectors of the economy seems critical in designing better policies aimed at enhancing growth.

In this article, we identify productivity linkages between the agricultural sector and 62 other sectors of the U.S. economy and measure short- and long-run productivity spillovers from and to the agricultural sector. Our results highlight how positive spillovers (synergies) across sectors can be exploited to optimize the cost efficiency of policy interventions to foster economic growth. Our results also highlight the need to abate negative intersectoral spillovers to avoid promoting productivity growth in one sector at the expense of others. These results are particularly relevant given the challenging decisions that U.S. policymakers face in reactivating the domestic economy in the aftermath of the coronavirus pandemic.

I. Estimation Methods

We investigate productivity spillovers along the agricultural supply chain by analyzing the historical pairwise association between a productivity measure in the agricultural sector and the same productivity measure for each of N non-agricultural sectors of the economy. The specific productivity measures employed in the present study are the logarithms of the historical time series for TFP and the partial productivities of labor (LPP) and capital (KPP). That is, using subscripts a to designate the agricultural sector, n to represent the non-agricultural sector, and t to denote time, our focus of attention are the productivity pairs $\{TFP_{a,t}, TFP_{n,t}\}$, $\{LPP_{a,t}, LPP_{n,t}\}$, and $\{KPP_{a,t}, KPP_{n,t}\}$ for each of the N non-agricultural sectors.

The appropriate way to model the pairwise association between productivity in the agricultural sector and productivity in the *n*th non-agricultural sector (for example, $\{TFP_{a,t}, TFP_{n,t}\}$) depends on whether the productivity series are characterized by unit roots. Therefore, the first step of the proposed approach is testing the null hypothesis of a unit root for each of the series. We use the method advocated by Elliott, Rothenberg, and Stock (1996), which they show to be more powerful than the standard Augmented Dickey-Fuller unit-root test (Dickey and Fuller 1979, 1981). To impose as few restrictions as possible, we allow for both a constant and a trend in the deterministic model used for detrending (which is required by the test). As explained in the "Results and Discussion" section, the null of a unit root cannot be rejected at standard levels of significance for the vast majority of the productivity series. In contrast, the unit-root null is strongly rejected for most series when tested using their first differences. Hence, we proceed under the assumption that all productivity series have a unit root but are stationary when first-differenced.

Given the aforementioned assumption about the time-series properties of the productivity data, in the second step, we estimate a vector autoregression (VAR) in levels (as opposed to first differences) for each pair of productivities (for example, $\{TFP_{a,t}, TFP_{n,t}\}$) to determine the appropriate number of lagged terms to include in the pairwise analysis (Pfaff 2008b). The estimated VARs include both a constant and a trend as deterministic regressors. The optimal number of lags is determined according to the Akaike information criterion (AIC) (Akaike 1974).

In the third step, we estimate a vector error-correction model (VECM) for each agricultural/non-agricultural productivity pair (for example, $\{TFP_{a,t}, TFP_{n,t}\}$), setting the number of lagged terms equal to the corresponding number of lags identified in the second step. The purpose of fitting this VECM is to test whether the productivity series in each pair are cointegrated. More specifically, for each productivity pair, we perform the Johansen cointegration trace test (Johansen 1995). Following the recommendations by Franses (2001), we allow for both a constant term and a trend in the cointegration relationship. For example, TFP in the agricultural sector and TFP in the *n*th non-agricultural sector are cointegrated if a coefficient β exists such that the series $e_{an,t}$, defined as:

$$e_{an,t} \equiv TFP_{a,t} - \beta TFP_{n,t} - \alpha_0 - \alpha_1 t \quad (1)$$

is stationary. In the above expression, α_0 and α_1 are coefficients, and t denotes time. Thus defined, cointegration between $TFP_{a,t}$ and $TFP_{n,t}$ means that TFP in agriculture and the nth non-agricultural sectors tend to move together toward the equilibrium value of (α_0 + $\alpha_1 t$), where the equilibrium value may be different from zero *(if* $\alpha_0 \neq 0$ *or* $\alpha_1 \neq 0$*)* and may have a deterministic trend *(if* $\alpha_1 \neq 0$*)*. The relevance of the cointegration analysis is that the existence of cointegration indicates a long-term relationship between the two series involved. That is, finding that productivity in agriculture and the non-agricultural sector are cointegrated allows us to conclude that they tend to move together in the long run.

Failure to find evidence of cointegration between two series characterized by unit roots suggests that they do not tend to move together in the long run. However, they may nevertheless exhibit joint short-term dynamics. If the null hypothesis of no cointegration is not rejected for a particular productivity pair, we investigate the existence of joint short-term dynamics by setting up a VAR in first differences and testing for Granger causality and instantaneous causality (Granger 1969; Lütkepohl 2006). For example, the first-difference VAR corresponding to the TFPs in agriculture and in the nth sector is:

$$\begin{aligned}\Delta TFP_{a,t} &= \sum_{k=1}^{K} \phi_{a,k} \Delta TFP_{a,t-k} + \sum_{k=1}^{K} \phi_{n,k} \Delta TFP_{n,t-k} + \phi_{a,0} + \phi_{a,trend} t + u_{a,t}, \\ \Delta TFP_{n,t} &= \sum_{k=1}^{K} \theta_{n,k} \Delta TFP_{n,t-k} + \sum_{k=1}^{K} \theta_{a,k} \Delta TFP_{a,t-k} + \theta_{n,0} + \theta_{n,trend} t + u_{n,t},\end{aligned} \quad (2)$$

where $\Delta TFP_t \equiv TFP_t - TFP_{t-1}$, ϕs and θs are coefficients, and the residuals $u_{a,t}$ and $u_{n,t}$ have variances of σ_a^2 and σ_n^2 and covariance of $\sigma_{a,n}$. In this instance, TFP in the nth sector does not Granger cause TFP in agriculture if and only if $\phi_{n,1} = \ldots = \phi_{n,K} = 0$. Analogously, TFP in agriculture does not Granger cause TFP in the nth sector if and only if $\theta_{a,1} = \ldots = \theta_{a,K} = 0$. Instantaneous causality exists if $\sigma_{a,n} \neq 0$. The optimal number of lags K in the first-difference VAR (2) is based on the AIC (Akaike 1974).

The cointegration test alone does not allow us to tell whether productivity shocks in each of the two sectors have permanent effects on both sectors, or whether a productivity shock in one sector affects the other sector's productivity permanently without the reverse being true. Furthermore, productivities in agriculture and in the *n*th non-agricultural sector may exhibit joint short-term relationships even if they are not cointegrated. In this instance, a productivity shock in one sector will have a short-term effect on the other sector's productivity that fades away over time. To analyze the nature of the short- and long-term relationships between each pair of productivities (for example, $\{TFP_{a,t}, TFP_{n,t}\}$), in the fourth and final step, we compute the impulse response function (IRF) for each productivity pair. IRFs are constructed based on the productivity pair's best-fitting VECM if the two series are cointegrated at the 5 percent significance level and on the best-fitting first-difference VAR (2) otherwise.

Estimation is performed in the R version 3.6.1 programming language and software environment. We use the package urca version 1.3-0 to test for unit roots and cointegration, and the package vars version 1.5-3 to select the optimum number of lags in the VARs, test for causality, and compute the IRFs (Pfaff 2008a, 2008b).

II. Data

Our main data set is the analytical KLEMS-type data used by Jorgenson, Ho, and Samuels (2017), henceforth "the JHS data."[5] Succinctly, the data contain the annual amounts of output, capital, labor, and materials in both nominal and real terms for each of the 65 industries in the U.S. National Income and Product Accounts from 1947 through 2014. This long time span is desirable, as it allows us to apply the proposed time series methods, many of which rely on asymptotic results for a large number of time series observations. Another desirable property of the data is that, being KLEMS-type, they are computed using harmonized definitions and aggregation procedures across industries—that is, individual series are comparable across industries because they are based on the same or similar definitions.

The JHS data set defines the agricultural sector as the "farms" industry. To allow for the possibility of stronger spillovers between agriculture and closely related sectors, we classify non-agricultural sectors into "ag-related" and "non-ag-related" sectors. Ag-related sectors comprise the following 10 industries: forestry, fishing and related activities;

wood products; furniture and related products; food and beverage and tobacco products; textile mills and textile product mills; apparel and leather and allied products; paper products; rail transportation; truck transportation; and food services and drinking places. Non-ag-related sectors comprise the 52 other industries excluding farms, federal general government, and state and local general government.[6]

The JHS data set does not report productivity measures per se. However, it allows us to construct TFP, LPP, and KPP indexes in a straightforward manner. We calculate the TFP index as the ratio of real output to real input, where real input is the Törnqvist input index obtained from the capital, labor, and intermediate input series in the database. We calculate the LPP index as the ratio of real output to real labor; similarly, we construct the KPP index as the ratio of real output to real capital. For all three indexes, we set the base year to 2010.

Although the JHS data set has several desirable properties for our analysis, the most widely used productivity series for agriculture are constructed by the U.S. Department of Agriculture (USDA 2020). The USDA series are available from 1948 to 2017, which overlaps almost entirely with the period for the JHS series. Hence, as a robustness check, we also analyze the pairwise association between productivities in agriculture and the 62 non-agricultural sectors using the USDA agricultural series, instead of the "farm" series from the JHS data set.

III. Results and Discussion

Table 1 summarizes the results from the unit root tests. Panel A shows that all of the agricultural productivity series fail to reject the null hypothesis of a unit root except for the TFP series from the JHS data. In contrast, all of the first-differenced agricultural productivity series strongly reject the unit root null, regardless of the productivity measure or the data set under consideration. Similarly, Panel B shows that the vast majority of non-agricultural productivity series cannot reject the unit root null, but do reject the null when first-differenced.[7] Overall, the results in Table 1 provide strong support for the assumption that productivity series are characterized by a unit root, and that the first-differenced series are stationary. Thus, we adopt this assumption for the remainder of the analysis.[8]

Table 1

Results of Unit-Root Tests Using the Elliott, Rothenberg, and Stock (1996) Method

Panel A: Results for Agricultural Productivities

Productivity	Series	Test statistics		Critical values at 10, 5, and 1 percent significance levels		
		JHS	USDA	10 percent	5 percent	1 percent
TFP	Level	−3.77	−2.33	−2.74	−3.03	−3.58
LPP	Level	−0.18	−0.96	−2.74	−3.03	−3.58
KPP	Level	−1.56	−1.09	−2.74	−3.03	−3.58
TFP	First-differenced	−4.86	−5.03	−2.74	−3.03	−3.58
LPP	First-differenced	−5.42	−5.44	−2.74	−3.03	−3.58
KPP	First-differenced	−4.69	−3.77	−2.74	−3.03	−3.58

Panel B: Results for Non-Agricultural JHS Productivities

Productivity	Series	Percentage of sectors (count/total) for which unit-root null is rejected at 10, 5, and 1 percent significance levels					
		Ag-related			Non-ag-related		
		10 percent	5 percent	1 percent	10 percent	5 percent	1 percent
TFP	Level	0.0 (0/10)	0.0 (0/10)	0.0 (0/10)	1.9 (1/52)	0.0 (0/52)	0.0 (0/52)
LPP	Level	10.0 (1/10)	10.0 (1/10)	10.0 (1/10)	5.8 (3/52)	3.8 (2/52)	0.0 (0/52)
KPP	Level	10.0 (1/10)	10.0 (1/10)	0.0 (0/10)	5.8 (3/52)	0.0 (0/52)	0.0 (0/52)
TFP	First-differenced	90.0 (9/10)	90.0 (9/10)	60.0 (6/10)	86.5 (45/52)	78.8 (41/52)	63.5 (33/52)
LPP	First-differenced	60.0 (6/10)	30.0 (3/10)	30.0 (3/10)	82.7 (43/52)	71.2 (37/52)	44.2 (23/52)
KPP	First-differenced	70.0 (7/10)	50.0 (5/10)	50.0 (5/10)	82.7 (43/52)	73.1 (38/52)	51.9 (27/52)

Notes: The deterministic model to detrend the series includes a constant and a trend. The estimated models include two lagged differences for the series in levels, and one lagged difference for the first-differenced series.
Sources: Jorgenson, Ho, and Samuels (2017) and USDA (2020).

Given the large number of pairwise productivity relationships we estimate, it is not practical to provide a detailed report or analysis by individual sectors. Thus, in the following subsections, we focus on the results that tend to apply to most sectors.

Total factor productivity

Table 2 reports the results of the cointegration tests. The first row reveals that agricultural TFP (measured using the JHS data set) is cointegrated with TFP in each of the 10 ag-related sectors at the 5 percent significance level over the 1947–2014 period. This result would seem to suggest strong long-term TFP spillovers between agriculture and ag-related sectors. However, the table also shows that agricultural TFP is cointegrated with TFP in all but one of the non-ag-related sectors at the 5 percent significance level over the same period. Together, these findings suggest that agricultural TFP tends to co-move with the TFPs of all sectors in the long run whether they are related to agriculture or not. In other words, the cointegration tests suggest that a sector's proximity to agriculture makes no difference to its TFP spillovers.

Charts 1 and 2 provide a graphic summary of the IRFs for the pairwise TFP relationships between agriculture and the other sectors. The pairwise relationships involving ag-related sectors are grouped on the left side of the solid vertical line, whereas those corresponding to the non-ag-related sectors are grouped on the right side. Within each group, a vertical dashed line separates sectors cointegrated with agriculture (left side) from sectors not cointegrated with agriculture (right side).[9] Sectors are listed in alphabetical order within subgroups.

The top two thirds of Chart 1 depict the 95 percent confidence intervals (CIs) for the one- and 10-year responses of non-agricultural TFPs to a shock to agricultural TFP. In contrast, the top two thirds of Chart 2 show the 95 percent CIs for the one- and 10-year responses of agricultural TFP to shocks in non-agricultural TFPs. The bottom third of Charts 1 and 2 show the number of years it takes to achieve 90 percent of the respective 10-year response. Below both charts are three rows of circles: the first row shows filled circles for sectors cointegrated with agriculture and empty circles otherwise. Filled and empty circles in the second and third rows denote whether the respective VECMs

Table 2
Sectors Exhibiting Pairwise Cointegrating Relationships with Agriculture

Productivity	Database	Percentage of sectors (count/total) exhibiting pairwise cointegrating relationships with agriculture at 5 percent significance level					
		Ag-related			Non-ag-related		
		Entire period	First half	Second half	Entire period	First half	Second half
TFP	JHS	100.0 (10/10)	40.0 (4/10)	50.0 (5/10)	98.2 (51/52)	48.1 (25/52)	46.2 (24/52)
LPP	JHS	80.0 (8/10)	10.0 (1/10)	20.0 (2/10)	28.8 (15/52)	15.4 (8/52)	11.5 (6/52)
KPP	JHS	40.0 (4/10)	60.0 (6/10)	60.0 (6/10)	15.4 (8/52)	48.1 (25/52)	67.3 (35/52)
TFP	USDA	90.0 (9/10)	40.0 (4/10)	40.0 (4/10)	88.5 (46/52)	36.5 (19/52)	48.1 (25/52)
LPP	USDA	50.0 (5/10)	0.0 (0/10)	50.0 (5/10)	21.2 (11/52)	28.8 (15/52)	73.1 (38/52)
KPP	USDA	30.0 (3/10)	90.0 (9/10)	40.0 (4/10)	17.3 (9/52)	63.5 (33/52)	40.4 (21/52)

Note: "Entire period" is 1947–2014 for JHS and 1948–2014 for USDA; "first half" is 1947–80 for JHS and 1948–80 for USDA; and "second half" is 1981–2014 for both JHS and USDA.
Sources: Jorgenson, Ho, and Samuels (2017) and USDA (2020).

(if cointegrated) or first-difference VARs (if not cointegrated) contain two or three lags.

Comparing the top two thirds of Chart 1 shows that the significant one-year responses are fewer and smaller in magnitude than their 10-year counterparts. According to the bottom third, typically no more than five years elapse to achieve 90 percent of the 10-year response. However, given the large percentage of sectors cointegrated with agriculture, the most striking finding from this chart is the small number of sectors that exhibit significant 10-year TFP responses to an agricultural TFP shock. Only four of the 10 ag-related sectors, or 40 percent, show a significant response to an agricultural TFP shock after 10 years. The share of non-ag-related sectors with a significant 10-year response is even lower (eight out of 52 sectors, or 15.4 percent). Among the significant 10-year responses, nine out of the 12 are positive, which suggests a tendency for significant 10-year responses to be positive.

Chart 1
Response of Non-agricultural Sectors' TFP to Shocks in Agricultural TFP

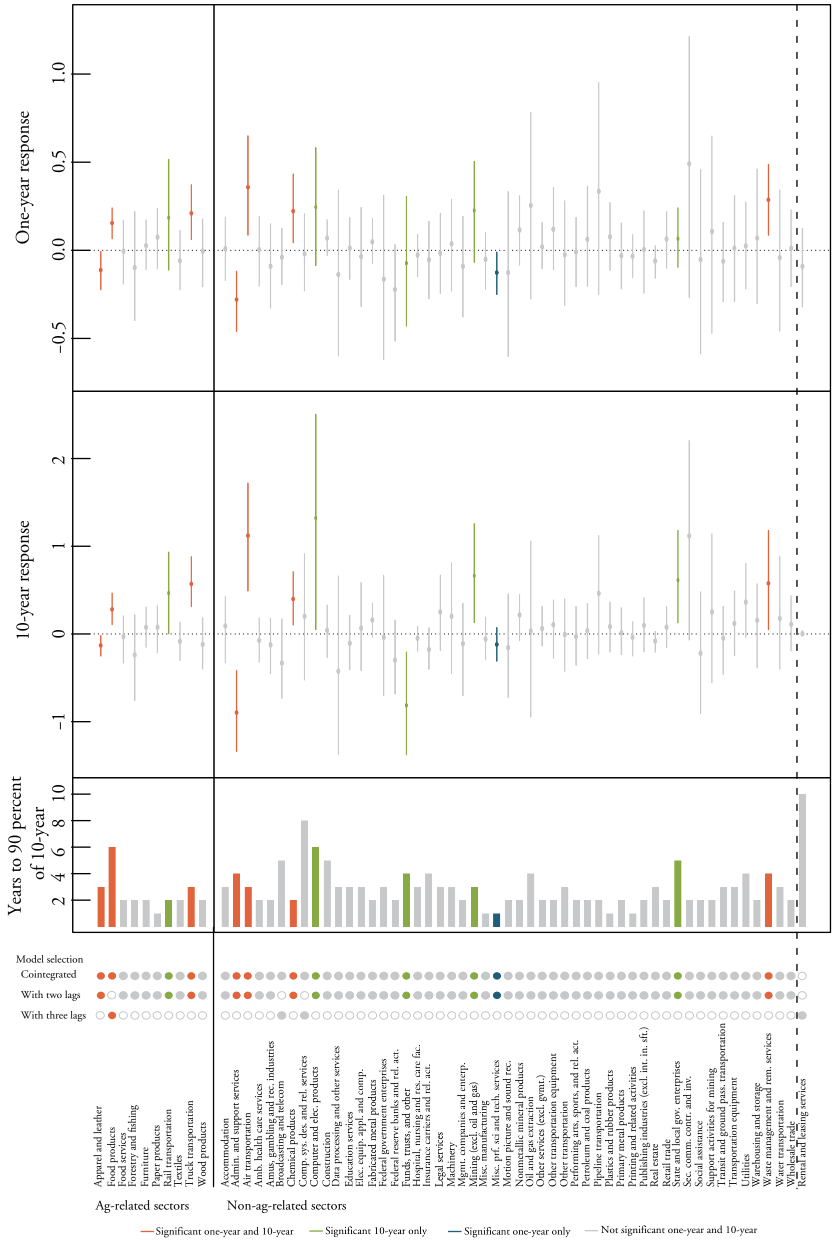
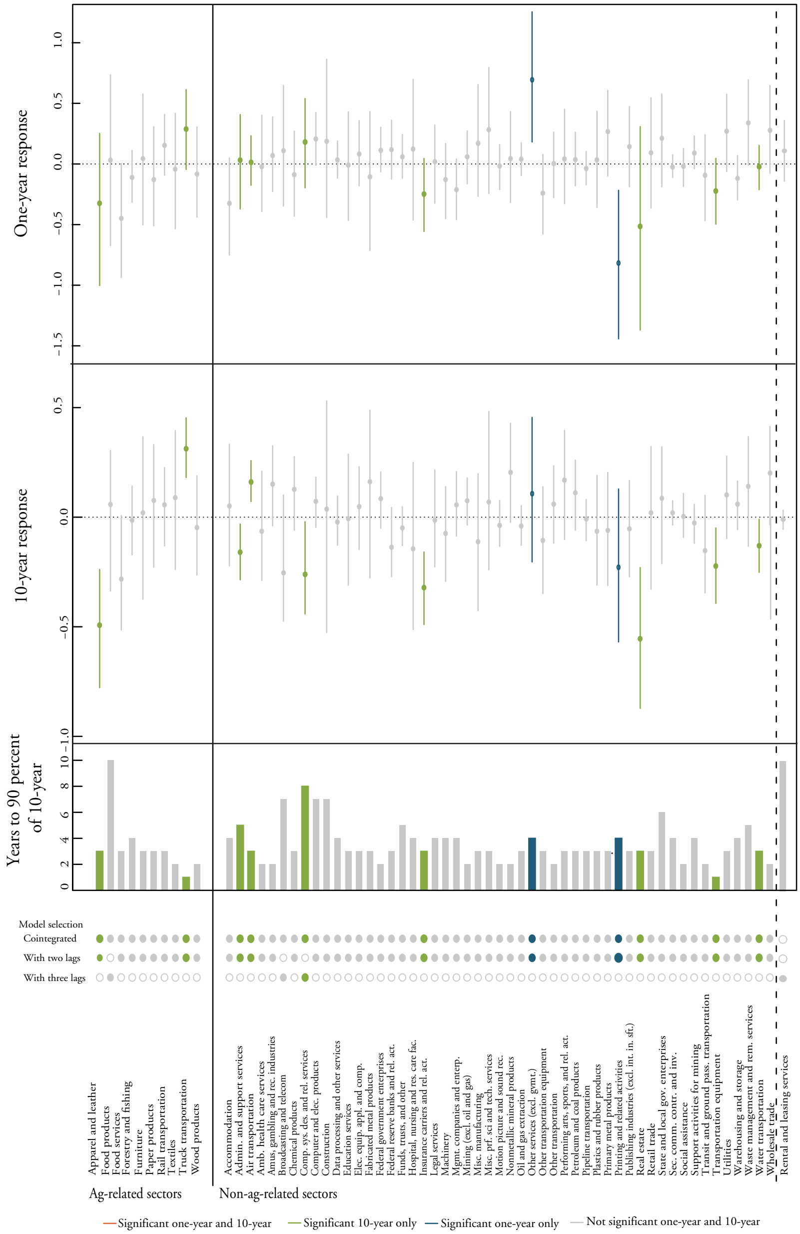


Chart 2
Response of Agricultural TFP to Shocks in Non-agricultural Sectors' TFP



Similar to Chart 1, the top two thirds of Chart 2 show that the significant one-year responses of agricultural TFP to non-agricultural TFP shocks are fewer and smaller in magnitude than the significant 10-year responses. As in Chart 1, Chart 2 reveals a major difference between the percentage of sectors cointegrated with agriculture (almost 100 percent) and the percentage of sectors whose shocks have a significant effect on agriculture after 10 years (less than 20 percent). Unlike Chart 1, however, Chart 2 shows a tendency for the significant 10-year responses to be negative, as seven out of nine bear a negative sign.

The first row of Table 3 shows that the only TFP pair with no evidence of cointegration does not exhibit Granger causality in either direction. Furthermore, the non-cointegrated TFP pair does not appear to be characterized by instantaneous causality, either. Both of these results are consistent with the shock responses depicted in Charts 1 and 2.

Overall, despite the strong evidence of pairwise TFP cointegration between agriculture and essentially all sectors reported in Table 2, Charts 1 and 2 demonstrate that TFP shocks in agriculture have a significant long-term effect on a relatively small number of sectors, and that in the long-term, agricultural TFP responds significantly to TFP shocks in only a handful of sectors. The significant long-term responses to agricultural TFP shocks have a slight tendency to be positive, whereas the opposite is true of the significant long-term responses of agriculture to TFP shocks in other sectors.

Partial productivity of labor

The second row of Table 2 shows that for LPP, 80 percent of ag-related sectors are cointegrated with agriculture at the 5 percent significance level over the 1947–2014 period compared with only 28.8 percent of non-ag-related sectors. The difference in the frequency of cointegration across the two groups is statistically significant, suggesting stronger LPP spillovers between agriculture and ag-related sectors than between agriculture and non-ag-related sectors.[10]

Remarkably, even though eight of the 10 ag-related sectors are cointegrated with agriculture, none of their LPPs have significant one- or 10-year responses to an agricultural LPP shock (Chart 3). Chart 4 shows an almost identical result for ag-related sectors' LPP

Table 3
Non-cointegrated Sectors Exhibiting Causal Relationships with Agriculture

Productivity	Database	Percentage of non-cointegrated sectors (count/total) exhibiting causal relationships with agriculture at 5 percent significance level					
		Ag-related sectors			Non-ag-related sectors		
		Granger causality		Instantan. causality	Granger causality		Instantan. causality
		Ag to non-ag	Non-ag to ag		Ag to non-ag	Non-ag to ag	
TFP	JHS	n/a	n/a	n/a	0.0 (0/1)	0.0 (0/1)	0.0 (0/1)
LPP	JHS	0.0 (0/2)	0.0 (0/2)	0.0 (0/2)	5.4 (2/37)	5.4 (2/37)	5.4 (2/37)
KPP	JHS	0.0 (0/6)	0.0 (0/6)	0.0 (0/6)	4.5 (2/44)	0.0 (0/44)	4.5 (2/44)
TFP	USDA	0.0 (0/1)	0.0 (0/1)	0.0 (0/1)	33.3 (2/6)	0.0 (0/6)	33.3 (2/6)
LPP	USDA	0.0 (0/5)	0.0 (0/5)	0.0 (0/5)	12.2 (5/41)	0.0 (0/41)	9.8 (4/41)
KPP	USDA	14.3 (1/7)	0.0 (0/7)	0.0 (0/7)	0.0 (0/43)	0.0 (0/43)	4.6 (2/43)

Note: Cells marked “n/a” denote that all pairs are cointegrated.
Sources: Jorgenson, Ho, and Samuels (2017) and USDA (2020).

shocks: agricultural LPP has no significant one-year responses to these sectors' shocks, and only one significant 10-year response.

Charts 3 and 4 demonstrate a noticeable, albeit less stark, contrast between the 28.8 percent of non-ag-related sectors cointegrated with agriculture and the much smaller percentages with significant one- and 10-year effects (see Table 2). An agricultural LPP shock yields a significant response at the one- and 10-year marks in only one of the 15 cointegrated non-ag-related sectors (see Chart 3). Similarly, LPP shocks in just three of the 15 cointegrated non-ag-related sectors have a significant effect on agricultural LPP after 10 years, and none have a significant effect at the one-year mark (see Chart 4).

The LPPs of non-cointegrated sectors—two of which are ag-related and 37 of which are non-ag-related—appear to be unrelated to agricultural LPP in the short term.[11] According to Chart 3, shocks to agricultural LPP yield a significant one-year response to LPP in only one non-cointegrated sector. Likewise, Chart 4 shows that shocks to LPP in only two non-cointegrated sectors yield a significant one-year response to agriculture LPP. The second row of Table 3 confirms these results, reporting a negligible percentage of pairs characterized by Granger causality or instantaneous causality.

Overall, few sectors have significant LPP responses to agricultural LPP shocks. The same can be said about the number of sectors whose LPP shocks significantly affect agricultural LPP. In fact, the small frequency of significant responses is consistent with what could be expected by pure chance. Thus, the significant responses we find may be an artifact of chance rather than meaningful economic relationships.

Partial productivity of capital

Out of the three productivities under examination, KPP has the fewest pairwise cointegrations from 1947 to 2014. According to the third row of Table 2, 40 percent of ag-related sectors and 15.4 percent of non-ag-related sectors exhibit KPP cointegration with agriculture, about half the shares observed for LPP. Although our results for KPP suggest that ag-related sectors are more likely to be cointegrated with agriculture than non-ag-related sectors, the difference is not significant at the 5 percent level.[12]

Chart 3
Response of Non-agricultural Sectors' LPP to Shocks in Agricultural LPP

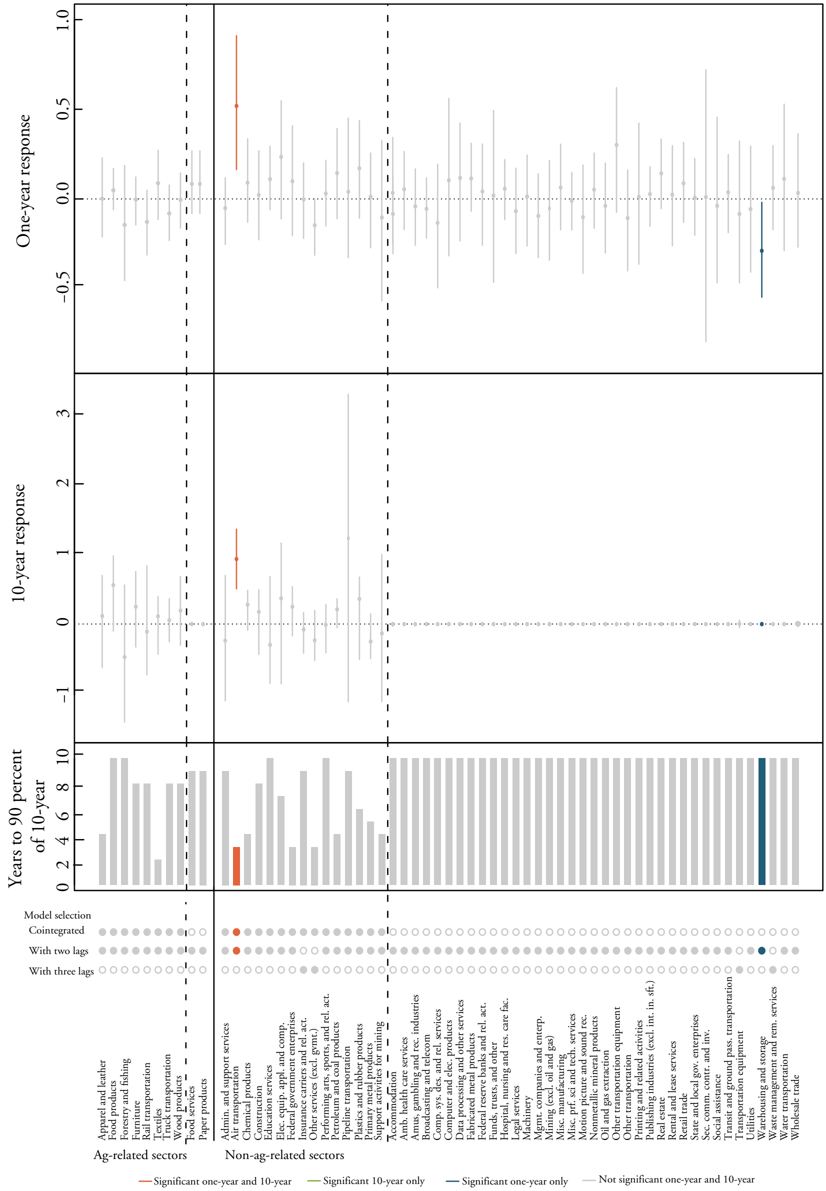


Chart 4
Response of Agricultural LPP to Shocks in Non-agricultural Sectors' LPP

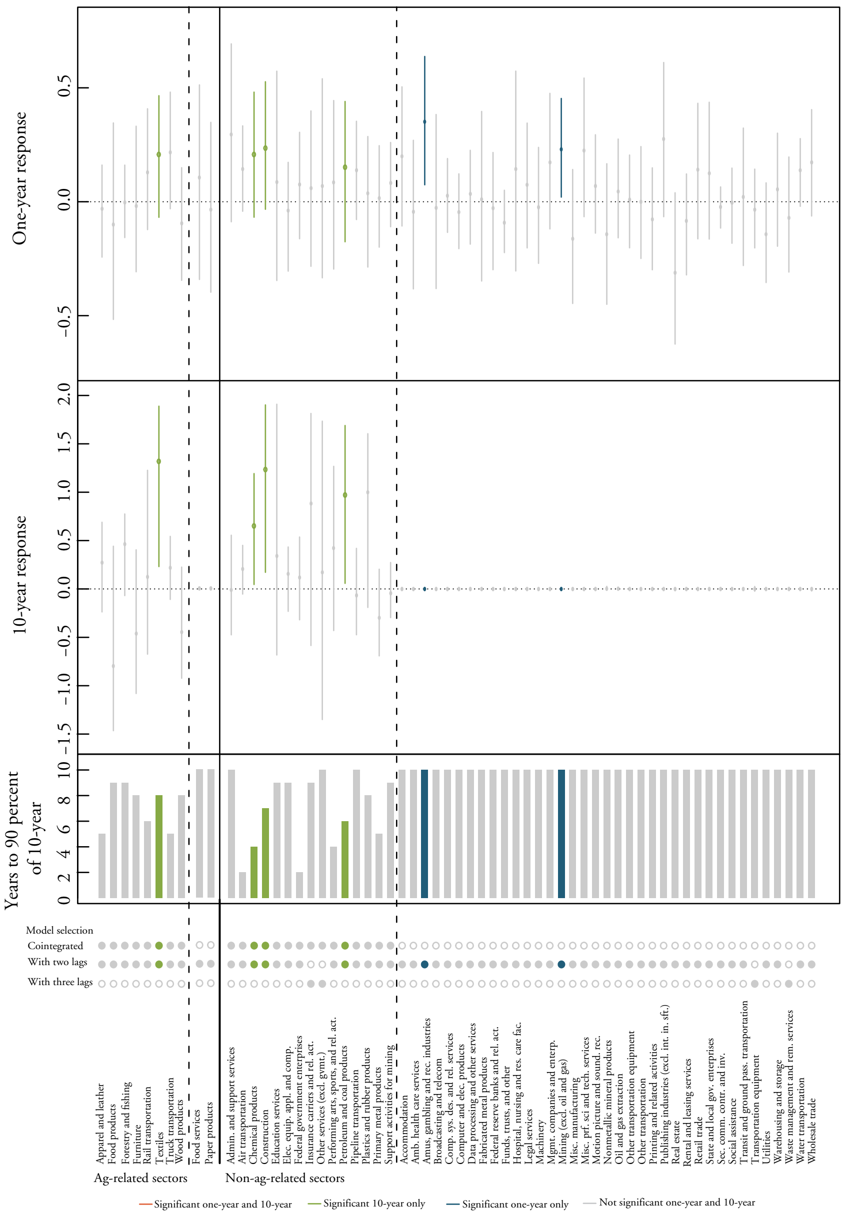


Chart 5 depicts the responses of ag-related and non-ag-related sectors' KPP to KPP shocks in agriculture. Only two ag-related sectors and one non-ag-related sector respond significantly after 10 years. Furthermore, only one sector, in the ag-related group, has a significant one-year response.

Chart 6 presents similar results for the responses of agriculture's KPP to KPP shocks in ag- and non-ag-related sectors. KPP shocks in only one ag-related sector exert a significant 10-year effect on agricultural KPP, and none exert a significant one-year effect. Likewise, KPP shocks in only one non-ag-related sector have a significant effect on agricultural KPP after both one and 10 years.

Strikingly, Charts 5 and 6 reveal that none of the non-cointegrated sectors (six ag-related and 44 non-ag-related) have statistically significant KPP relationships with agriculture after one year. The third row in Table 3 provides additional evidence regarding the lack of short-term pairwise KPP relationships between agriculture and other sectors. The number of non-cointegrated pairs characterized by Granger causality or instantaneous causality is zero for the ag-related group and negligible for the non-ag-related group.

In summary, the evidence for KPP suggests very few, if any, significant short- or long-term spillovers from agriculture to other sectors, or vice-versa.

IV. Have Agricultural Productivity Spillovers Changed over Time?

Thus far, our empirical analysis has assumed that the pairwise productivity relationships between agriculture and other sectors remained constant over the 1947 to 2014 period covered by the JHS data. However, this period was characterized by substantial changes in technology, demography, regulations, and policies that all likely influenced the economic structure of the sectors under analysis. Thus, it is reasonable to hypothesize that the pairwise productivity relationship between agriculture and a particular sector may have shifted over time, rendering our previous analysis too restrictive. For this reason, we also conduct separate empirical analyses for two subperiods: 1947–80 and 1981–2014.

Table 2 reveals that for both TFP and LPP, estimations over subperiods yield fewer significantly cointegrated pairs. In the case of TFP, only about half of the cointegration relationships that are significant over the entire period are also significant in the individual subperiods

Chart 5

Response of Non-agricultural Sectors' KPP to Shocks in Agricultural KPP

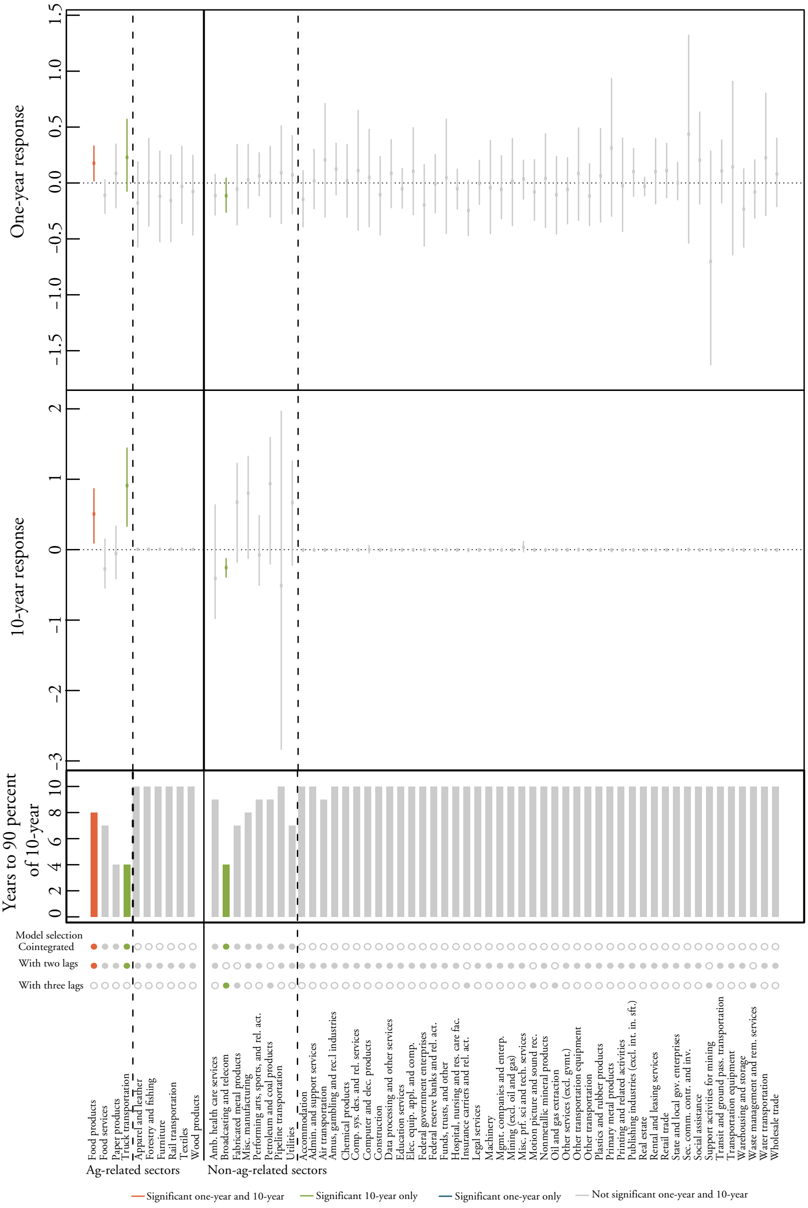
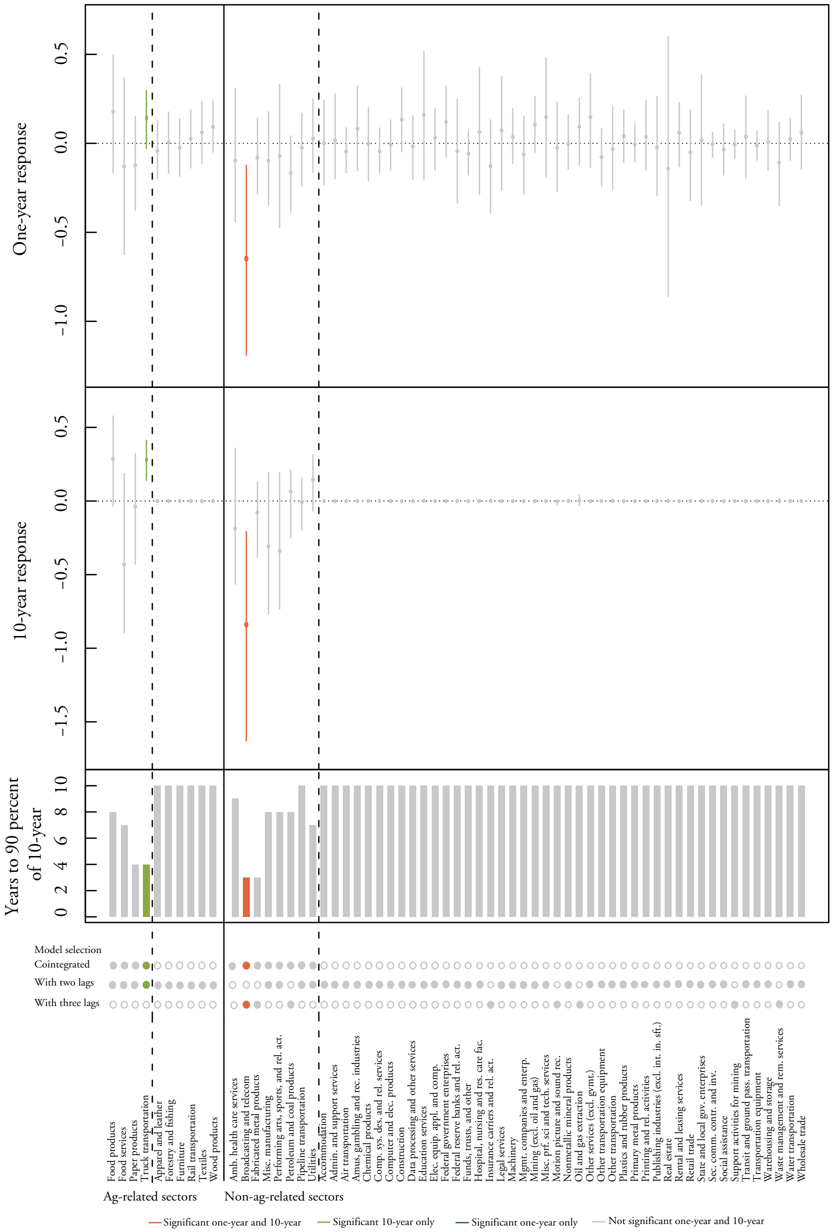


Chart 6
Response of Agricultural KPP to Shocks in Non-agricultural Sectors' KPP



1947–80 or 1981–2020. The number of significant LPP relationships between agriculture and non-ag-related sectors also drops by about half after breaking down the sample into two subperiods, and the drop is even more pronounced for LPP relationships between agriculture and ag-related sectors. These results for TFP and LPP are consistent with relatively stable but not particularly strong cointegrating relationships over the entire 1947–2014 period: cutting the number of observations in half for the subperiod analysis reduces the precision of the estimates, thereby weakening the evidence against the null hypothesis of no cointegration to the point where it may no longer be rejected.

In contrast, many more pairwise KPP relationships are significantly cointegrated over the 1947–1980 or 1981–2014 subperiods than over the full 1947–2014 sample (see Table 2). The greater number of cointegrated KPP relationships in the subperiods than the full sample implies that KPP relationships changed substantially over time. Relationships over the subperiods must have been relatively strong to reject the null of no cointegration, because subperiod estimates rely on fewer observations and are, all else equal, less precise than the full-period estimates. If such strong relationships had been sustained over time, they would have led to even stronger rejections of the no-cointegration null when using the entire sample; instead, the full-sample estimates weakened the evidence of cointegration.

In the interest of space, the subperiod equivalents of Charts 1 through 6 and Table 3 are omitted, as they do not provide valuable additional insights. To summarize, the productivity data suggest that the relationship between agriculture and other sectors was not particularly strong and remained relatively stable over the full period analyzed for TFP and LPP. For KPP, however, evidence suggests that the relationship between agriculture and other sectors experienced major shifts between 1947 and 2014.

V. Robustness Check: Pairwise Relationships Using USDA Agricultural Productivity Data

Shumway and others (2017) compare agricultural TFP measures from an earlier version of the JHS database with the 2014 version of the official TFP series published by the USDA. They find that, despite the methodological differences, the series are remarkably similar in terms of the average growth rates of agricultural TFP over 1948–2010 and the four selected subperiods (1948–73; 1973–95; 1995–2005; 2005–10). In this section, we extend the comparison period and assess TFP, KPP, and LPP spillovers between agriculture and the other sectors of the economy from 1948 to 2014.

Johansen cointegration tests over the entire 1948–2014 period show that the USDA and JHS data are similar for agricultural TFP but different for KPP. For the TFP series, the tests reject the null of no cointegration at the 1 percent significance level. For the LPP series, the evidence of cointegration is somewhat weaker: the tests reject the null of no cointegration at the 5 percent (but not 1 percent) significance level. In contrast, the KPP series shows no evidence of cointegration between the JHS and USDA data over the 1948–2014 period: the tests do not reject the no-cointegration null even at the 10 percent significance level. Overall, these cointegration results suggest that inferences drawn from the USDA data will be most similar to those drawn from the JHS data for TFP and most different for KPP.

The results from the pairwise cointegration tests in Table 2 indicate that the USDA database yields similar cointegration patterns for 1948–2014 to those in the JHS agricultural productivity data. That is, regardless of whether one relies on the JHS or the USDA data, TFP has the largest number of cointegrated pairs, while KPP has the fewest. However, for the non-ag-related group, the USDA data yield fewer cointegrated pairs than the JHS data in all instances other than KPP.

In the interest of space, graphs analogous to Charts 1 through 6 are included in the Appendix, as they exhibit similar patterns. Table 3 demonstrates that the non-cointegrated pairs for the USDA data show short-term causal relationships similar to those already described for the baseline data set. Overall, the USDA agricultural productivity data reinforce the results obtained using the JHS agricultural productivity data over the entire overlapping period.

Breaking down the sample period into halves suggests that the JHS and USDA series for TFP and LPP maintain a stable but not particularly strong relationship from 1948 to 2014. In both cases, tests reject the null of no cointegration for the entire overlapping period, but cannot reject the null even at the 10 percent significance level for one of the subperiods. Contrastingly, the relationship between the JHS and USDA series for KPP appears to have changed significantly over time. Although tests do not reject the null hypothesis of no cointegration over the entire 1948–2014 period at standard levels of significance, they do reject the null for each of the subperiods.

According to Table 2, the subperiod estimation using the USDA agricultural productivity data yields similar results to the subperiod estimation using JHS data for TFP and KPP. Specifically, when compared with the full period estimation, both subperiod estimations yield fewer significantly cointegrated pairs for TFP and more significantly cointegrated pairs for KPP. For LPP in non-ag-related sectors, however, the results differ. Specifically, the subperiod estimation using the USDA series yields more significantly cointegrated pairs than the estimation using the JHS data. In short, the subperiod analysis based on the USDA data provides additional support for two conclusions drawn earlier from the JHS data: first, that TFP was characterized by relatively stable but not strong cointegrating relationships over the full sample period; and second, that KPP relationships underwent substantial changes over time. However, the subperiod analysis using USDA data yields a finding for LPP that conflicts with the analysis using JHS data: the USDA data suggest major shifts in LPP relationships between 1948 and 2014, but the JHS data suggest steady but not strong relationships over time.

VI. Conclusion

The present study is the first to explore the linkages between the agricultural sector and 62 other sectors of the U.S. economy from a productivity perspective from 1947 to 2014. Applying widely adopted time series methods to productivity measures derived from JHS, our analysis suggests that increasing (reducing) TFP in agriculture above (below) trend would negatively (positively) affect the TFP of three sectors and positively (negatively) affect the TFP of five sectors after one year, but generate long-lasting increases (reductions) in the TFP of nine sectors and lasting reductions (increases) in the TFP of three sectors. Shocks in the TFP of two sectors would spill over into the agricultural sector after one year (one with same sign, and the other with the opposite sign), and shocks in the TFP of nine sectors would have significant spillover effects into the agricultural sector after 10 years (two with the same sign, and seven with the opposite sign). Our results also suggest that the few significant LPP and KPP spillovers across sectors may be an artifact of chance, and that labor and capital productivity in the agricultural sector are unrelated to their counterparts in the rest of the U.S. economy.

Comparing the results obtained over the entire sample period against those from the 1947–80 and 1981–2014 subperiods reveals that the relationship between agriculture and other sectors was stable but not particularly strong for TFP and LPP. For KPP, however, the relationship between agriculture and other sectors changed substantially between 1947 and 2014. In any case, it is important to note that partial productivity measures like LPP and KPP might be highly sensitive to shifts in input mixes over time and therefore provide less reliable information on productivity change than TFP.

Our findings can help policymakers exploit intersectoral synergies and mitigate negative intersectoral spillovers to revive economic growth in the U.S. agricultural sector over the next decade. Furthermore, our approach can be applied to estimate the economy-wide effects of a specific policy designed to foster productivity growth in one sector of the economy. For example, our approach allows for the incorporation of spillover effects beyond the agricultural sector into the calculation of the social rate of return to public investments in agricultural R&D (and other productivity-enhancing public goods). Following Coe and Helpman (1995), our estimates can be used as weights in the calculation of an aggregate economic return in the rest of the economy stemming from the initial investment in the agricultural sector.

Our qualitative results are robust to the use of the USDA TFP series instead of the JHS TFP series for the agricultural sector, reinforcing the conclusion from Shumway and others (2017) that, despite methodological differences, TFP growth estimates from the two databases are remarkably similar. Qualitative results for LPP and KPP are also similar when using the USDA data instead of the JHS series. However, in the case of LPP, the analysis based on the USDA series suggests that the relationships changed over time, contradicting the stable but not strong relationships implied by the JHS data.

Although our analysis was not designed to measure the degree of convergence in productivity changes across sectors, our results tangentially inform such discussion by evaluating the cointegration in productivity series across sectors. In particular, we find no significant cointegrating vectors across agriculture and 50 other sectors in KPP, 39 other sectors in LPP, and one other sector in TFP, suggesting that those pairs of productivity series do not converge in time series (Bernard and Durlauf 1995). However, further analysis is required to evaluate whether two cointegrated productivity measures imply convergence in time series (depending on the significance of the coefficient α_1 in equation (1)).

A major limitation of our empirical investigation resides in the top-down approach of the sectoral productivity comparisons. A future bottom-up study on the micro fundamentals for the sectors displaying significant productivity spillovers from and to agriculture is warranted to provide insights on the microeconomic foundation of the observed sectoral relationships. Another major limitation is the level of aggregation of the JHS data at the national level, which prevents richer state- or region-specific analyses.

Appendix
Supplementary Charts

Chart A-1
Response of JHS Non-agricultural Sectors' TFP to Shocks in USDA's Agricultural TFP

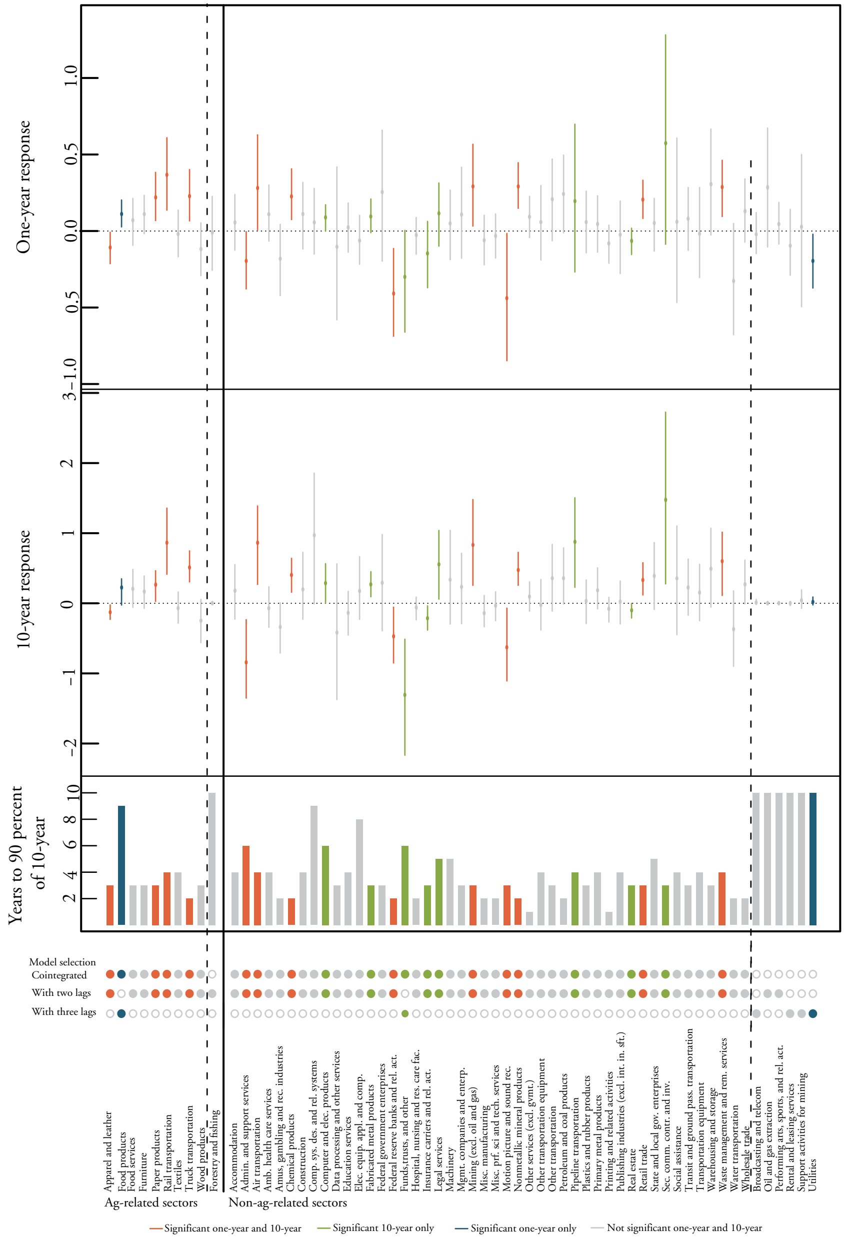


Chart A-2
Response of USDA's Agricultural TFP to Shocks in JHS Non-agricultural Sectors' TFP

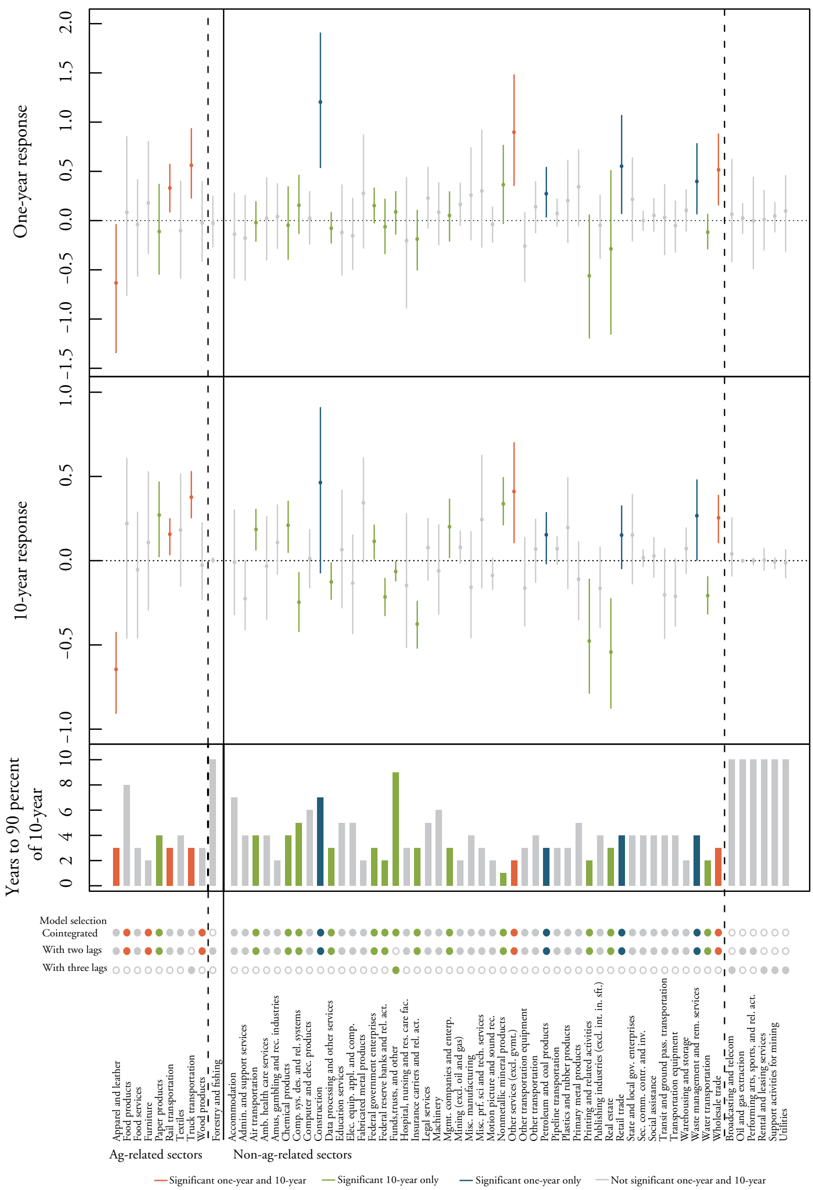


Chart A-3
Response of JHS Non-agricultural Sectors' LPP to Shocks in USDA's Agricultural LPP

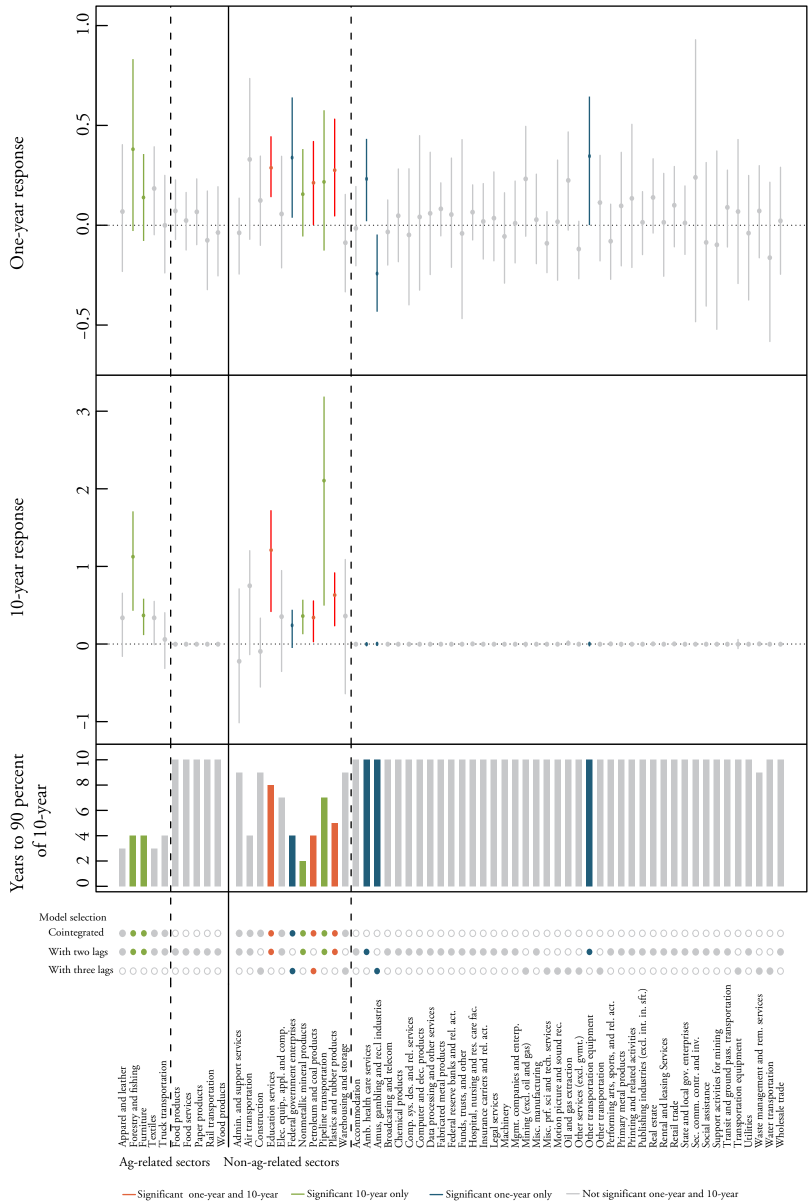


Chart A-4

Response of USDA's Agricultural LPP to Shocks in JHS Non-agricultural Sectors' LPP

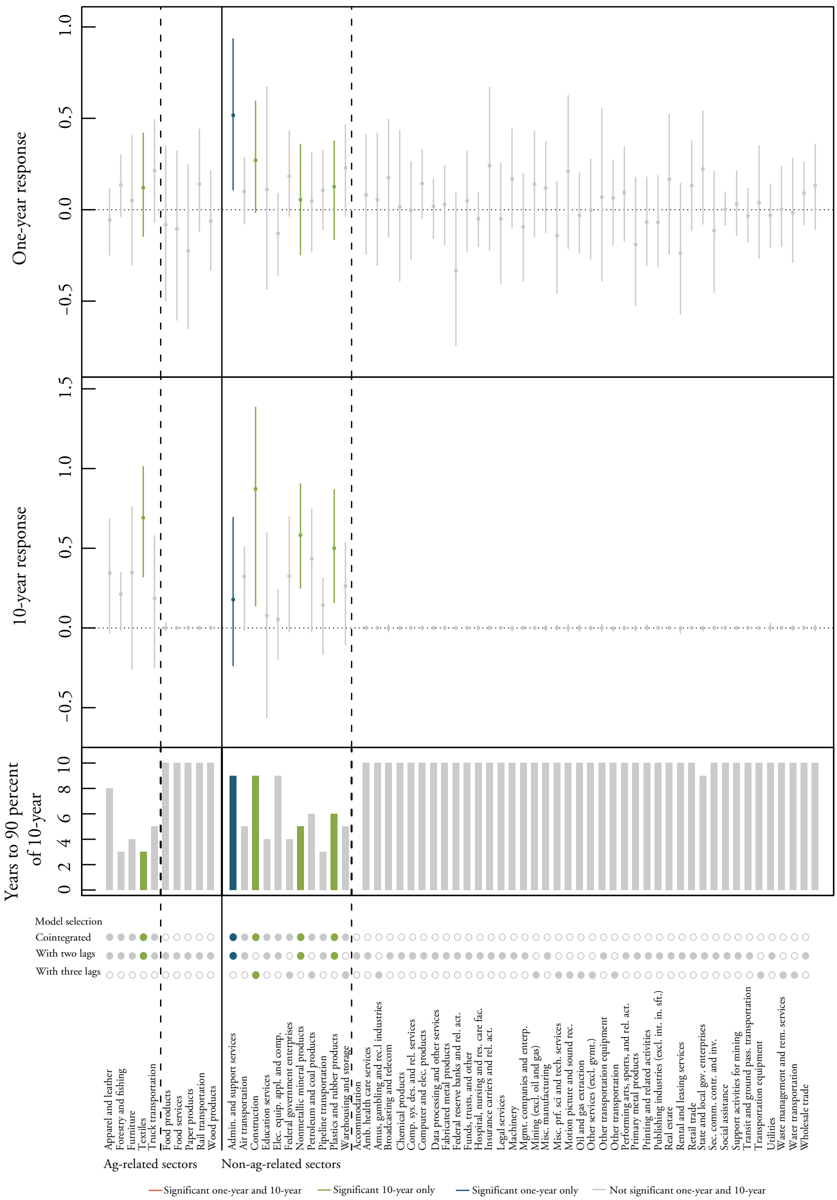


Chart A-5

Response of JHS Non-agricultural Sectors' KPP to Shocks in USDA's Agricultural KPP

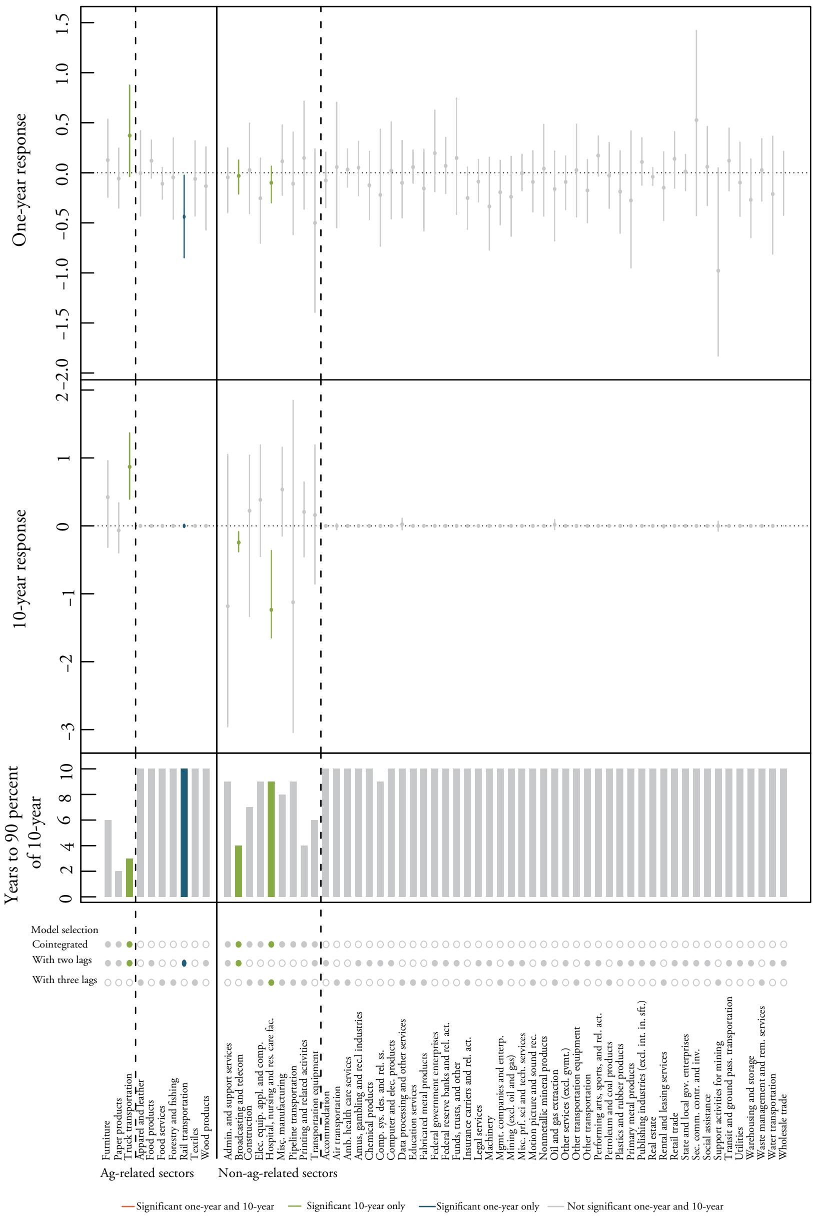
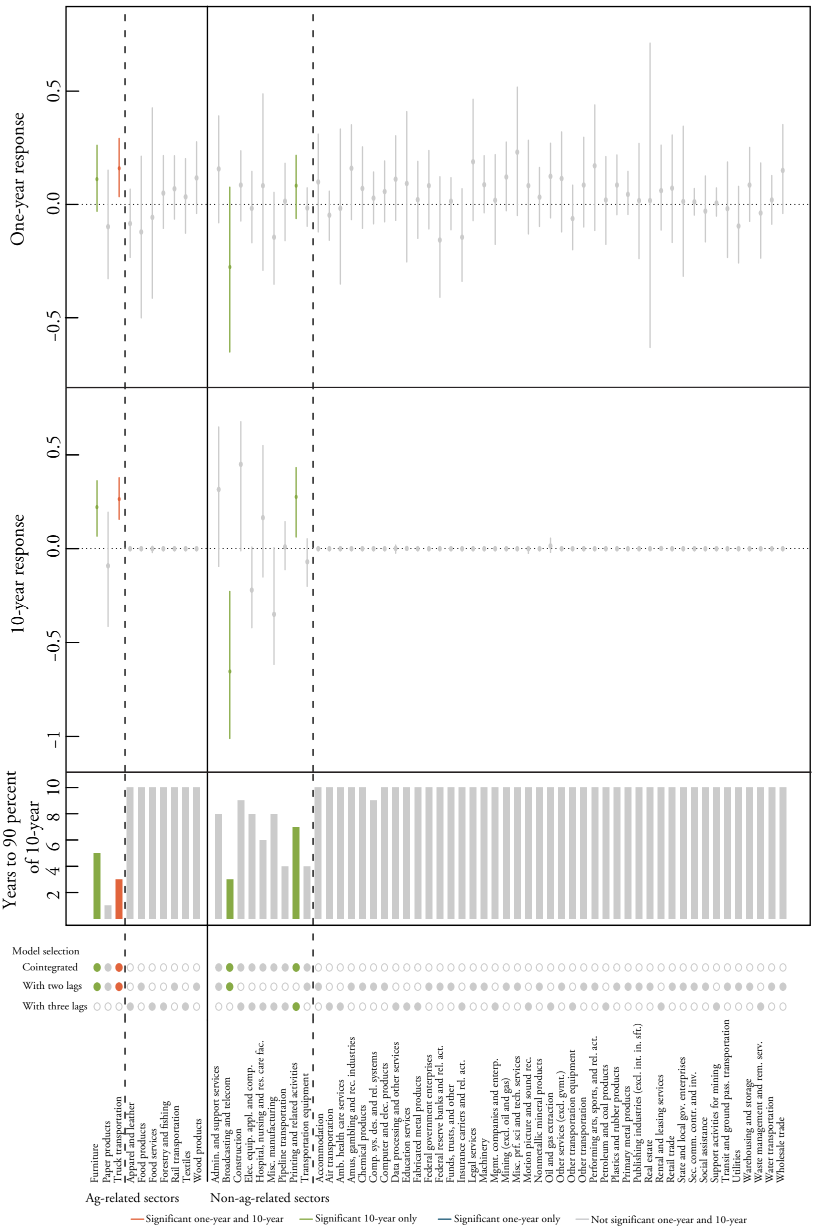


Chart A-6
Response of USDA's Agricultural KPP to Shocks in JHS Non-agricultural Sectors' KPP



Endnotes

[1]TFP has been shown to be a major source of agriculture growth in both state and national level data sets. On the state level, for example, see Craig and Pardey (1990a, 1990b); Huffman and Evenson (1989, 1993); Alston and Pardey (1996); Ball and others (1999); Acquaye, Alston, and Pardey (2003); O'Donnell (2012); Njuki, Bravo-Ureta, and O'Donnell (2018); Plastina and Lence (2018); Chambers and Pieralli (2020). On the national level, see USDA (1981); Ball (1985); Hauver (1989); Jorgenson and Gollop (1992); Ball and others (1997); Wang and others (2015).

[2]Garner and others (2019) use the concept of multifactor productivity instead of TFP in their analysis.

[3]The studies that disaggregate TFP in U.S. agriculture into technological changes; productive, allocative, and scale efficiencies; as well as price effects include Capalbo (1988); Morrison Paul and Nehring (2005); Andersen, Alston, and Pardey (2012); O'Donnell (2012, 2014); Plastina and Lence (2018); Njuki, Bravo-Ureta, and O'Donnell (2018); and Chambers and Pieralli (2020). Wang and others (2015), Fuglie and others (2017), Alston (2018), and Baldos and others (2019) provide recent reviews of the literature on research and development, extension services, knowledge spillovers, and communication and transportation infrastructure as major drivers of agricultural productivity. Earlier comprehensive literature reviews on the returns to productivity-enhancing investments in U.S. agriculture include Alston and others (2000); Huffman and Evenson (2006); Fuglie and Heisey (2007); Alston and others (2010); and Hurley, Rao, and Pardey (2014).

[4]Studies on knowledge spillovers from other sciences into agriculture include Huffman and Evenson (2006); Shoemaker and others (2001); and Wang, Xia, and Buccola (2009). Studies on knowledge spill-ins to agricultural productivity from agricultural R&D conducted in other jurisdictions include Coe and Helpman (1995); Schimmelpfennig and Thirtle (1999); Huffman and others (2002); Alston and others (2010); and Plastina and Fulginiti (2011).

[5] The acronym KLEMS stands for capital (K), labor (L), energy (E), materials (M), and services (S). Analytical KLEMS-type data are constructed by researchers in the WORLD KLEMS consortium; they have harmonized definitions and aggregation procedures so as to obtain industry-level productivity measures that are comparable across countries. The data are available online at http://www.worldklems.net/data.htm

[6]We exclude the federal general government and state and local general government industries from the analysis because their TFPs are constant for the entire period, yielding nonsensical regression estimates.

[7]Although the Elliott, Rothenberg, and Stock (1996) test is more powerful than the standard augmented Dickey-Fuller unit-root test, unit-root tests have

low power in general (that is, they have a low probability of correctly rejecting the null hypothesis of a unit root when in fact the series is stationary) (Enders 2014).

[8]Cointegration between two series requires that each of them be characterized by a unit root. Hence, if JHS's agriculture TFP series is assumed to be stationary, one should immediately conclude that it is not cointegrated with any of the non-agricultural sectors' TFPs.

[9]There is no dashed line within the ag-related group in Charts 1 and 2 because all ag-related sectors are cointegrated with agriculture in the case of TFP. In contrast, Charts 3 through 6 depict dashed lines within the ag-related group because not all of its sectors have partial productivities cointegrated with agriculture's.

[10]We use the exact test from Fisher (1954) to assess whether the probability of cointegration is the same for ag-related as for non-ag-related groups. For the test, we use the 2 x 2 contingency table consisting of eight cointegrated pairs and two non-cointegrated pairs for the ag-related group, and 15 cointegrated pairs and 37 non-cointegrated pairs for the non-ag-related group. The test rejects the null hypothesis of equal probabilities at the 0.4 percent significance level.

[11]These sectors cannot have long-term relationships with agricultural LPP because they are not cointegrated.

[12]Given the 2 x 2 contingency table consisting of four cointegrated pairs and six non-cointegrated pairs for the ag-related group and eight cointegrated pairs and 44 non-cointegrated pairs for the non-ag-related group, the exact test from Fisher (1954) rejects the null hypothesis of equal probabilities at the 9.1 percent significance level.

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Environmental Drivers of Agricultural Productivity Growth and Socioeconomic Spillovers

By Wolfram Schlenker

Agricultural productivity has risen sharply since World War II. Corn yields, for example, fluctuated around a fairly stable average between 1866, the first year for which the National Agricultural Statistics Service (NASS) provides data, and about 1940. Since 1940, however, corn yields have trended steadily upward.

Chart 1 shows average annual U.S. corn yields as well as their trend. From 1940 to 1980, yields grew exponentially, as shown by the linear increase in the blue solid line—that is, there was a linear trend in log yields. This finding is consistent with Jorgenson and Gollop (1992), who examine total factor productivity growth (TFP) in U.S. agriculture over the 1947–1985 period. They find that although employment in the agricultural sector decreased by 1.8 percent per year over that period, output increased. They conclude that "there is little doubt that the role of productivity growth in agriculture is quite different than in the rest of the economy. … agriculture's average annual rate of TFP growth has been nearly four times as large as the corresponding rate in the rest of the economy." This exponential increase seems to be leveling off: starting around 1980, absolute corn yields have been growing linearly (orange solid line), while the trend in log yields is starting to decrease.

Despite tremendous gains in agricultural productivity, the sector remains as vulnerable to environmental factors as ever. The dashed blue line in Chart 1 shows that the deviations from the log trend seem to have rather constant variance over time. In other words, the year-to-year

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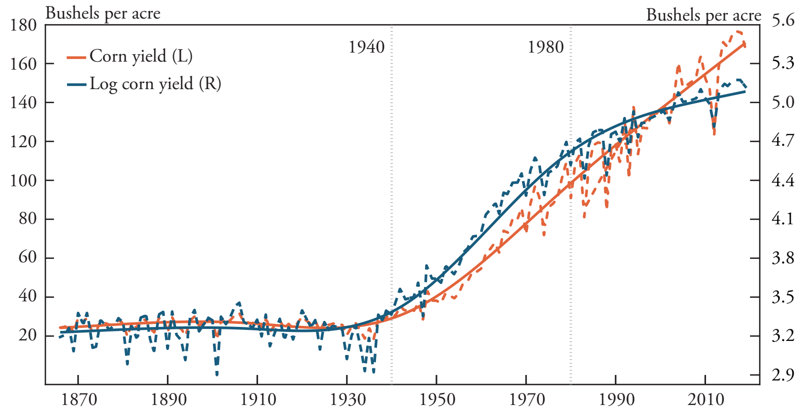
Chart 1
United States Average Corn Yields, 1866–2019



Notes: Dashed lines denote year-to-year fluctuations, while solid lines denote trends. Trends are estimated using restricted cubic splines with five knots between 1966 and 2019.
Sources: USDA NASS, NOAA, and author's calculations.

swings in yields are constant in percent terms. As average yields have increased, so, too, has the standard deviation of the fluctuations around them. Most of the fluctuations around the trend are caused by environmental factors such as weather, air pollution, or pest outbreaks. The constant percent variation around the mean implies that agriculture is as dependent on environmental factors today as it has been historically.

In this paper, I document agriculture's dependence on two specific environmental factors: weather—in particular, extreme heat—and ozone air pollution. As I will show in Section I, in both cases, it is crucial to look not just at the average outcomes but also at extremes, which have a large measurable effect on observed yields. Section II highlights recent trends in these environmental factors over the last 40 years as well as how they contributed to the observed yield trend. Extreme heat is predicted to increase in future years, although the observed time series does not yet bear this out. An increase in extreme heat would likely depress future yield growth. Peak ozone pollution has been almost entirely phased out over the sample period, contributing significantly to the observed yield trend. However, because peak ozone pollution has been eliminated, no further reductions with beneficial effects on future yield growth are feasible. Finally, Section III outlines the socioeconomic spillovers from productivity growth on rural areas, documenting how past episodes of productivity shocks have led to outmigration from rural to urban areas.

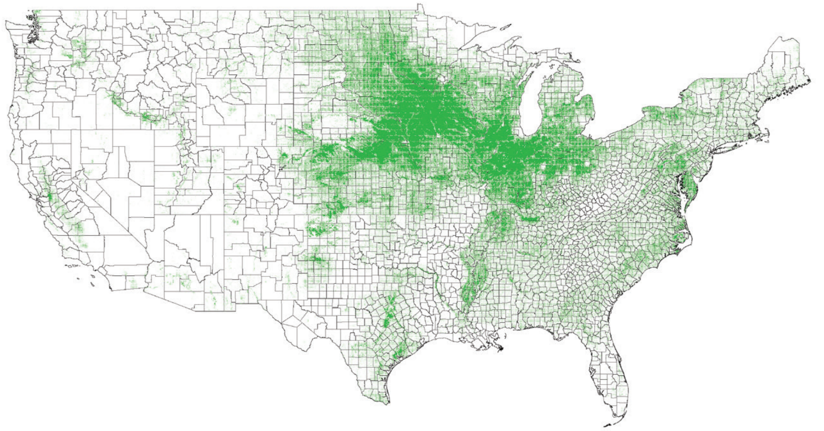
I. Effect of Weather and Ozone on Corn Yields

Corn is the crop with the largest growing area in the United States. This section demonstrates the importance of two environmental effects on corn yields: weather and ozone pollution. The weather variable specification and implementation follow Schlenker and Roberts (2008), while the ozone variables follow Boone, Schlenker, and Siikamäki (2019). Both analyses focus on the importance of nonlinear effects: because averaging over time or space can dilute such nonlinear effects, the micro-level data are constructed on a roughly 2.5 x 2.5 mile grid.

Map 1 displays the average corn area from the cropland data layer from 2010 to 2018 aggregated to the same 2.5 x 2.5 mile grid (1/24th degree latitude and longitude) as the weather data. The green coloring within each grid cell is proportional to the corn growing area in that cell: if 50 percent of the grid area grows corn, half of the square is colored green. The Corn Belt is clearly visible, but corn is also grown in most of the remaining counties in the United States—though sometimes only in a small subarea. County boundaries are delineated in black.

All weather and pollution variables are first derived for each grid before they are averaged over a county. If the underlying relationship is nonlinear, it is important to first derive the nonlinear transformation on a fine temporal and spatial scale before aggregating the data, as two days (or two points) with similar average temperature (or pollution) can have very different maximums and minimums. For example, consider two counties that both have an average ozone pollution level of 70 parts per billion (ppb). If the first county has a pollution level of 70 ppb in all of its grid points, it would never exceed the critical value of 70 ppb that is harmful for crops and thus the pollution would not result in any damage to the corn crop in a county. On the other hand, if the second county has an ozone pollution of 40 ppb in half of its grid points and 100 ppb in the other half—with a county average of 70 ppb—a substantial portion of the country would be above the threshold of 70 ppb, resulting in a yield reduction in that area that should show up in the aggregate county statistic.

Map 1
Average Corn Area, 2010–18



Sources: USDA NASS Cropland Data Layer and author's calculations.

Hourly air pollution data are available from the Environmental Protection Agency (EPA) Ambient Air Quality Monitoring Program and Data starting in 1980.[1] Following Boone, Schlenker, and Siikamäki (2019), missing hourly values are filled in by cross-interpolation and then interpolated to the above 2.5 x 2.5 mile grid before being averaged over all grids in a county using the average corn area in the cropland data layer for the years 2010–18. The area weights are purposefully kept constant across years to not confound the analysis with possibly endogenous changes in where crops are grown. Similarly, minimum and maximum temperatures, as well as degree days, are derived for each grid and day following Schlenker and Roberts (2008) before being aggregated to the county level. Weather variables keep the set of weather stations constant to derive year-to-year weather shocks that are not driven by compositional changes. As Dell, Jones, and Olken (2014) point out, such year-to-year weather shocks are exogenous and hence form the ideal right-hand-side variable.

The analysis matches pollution and weather data with county-level corn yields from NASS for counties east of the 100-degree meridian excluding Florida from 1980 to 2019. Only counties that report corn yields in at least 20 of the 40 years of the sample are included, which includes all major production areas. The exact specification uses a panel analysis relating log corn yields in a county and year to two temperature variables, two precipitation variables, and one measure of ozone pollution in the same year aggregated over the 183-day period from April 1 to September 30.

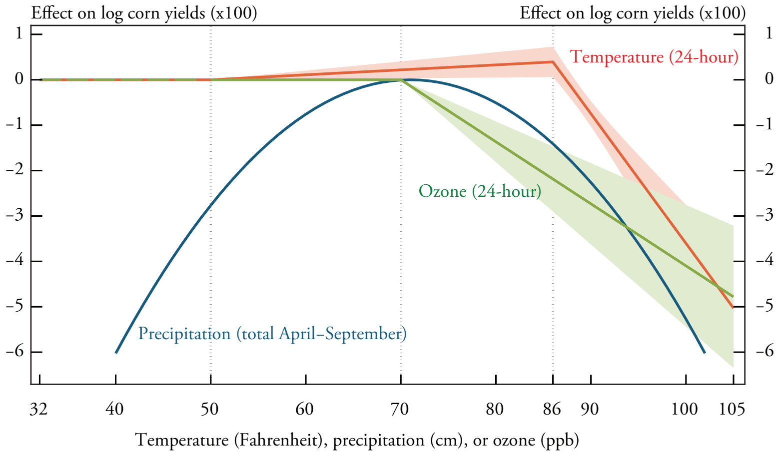
The specification also includes county fixed effects to allow for differences in average productivity, year fixed effects to absorb common price shocks, and county-specific quadratic time trends to allow for the fact that yields have been trending upward differently over the sample period. Errors are clustered at the state to allow for spatial correlation. Chart 2 shows the results. The vertical axis shows the effect on annual log yields multiplied times 100, so that each number roughly represents percent effects. I discuss each of the five environmental variables in turn.

The first two variables are for precipitation. The blue line shows point estimates for the quadratic in season-total precipitation. Both the linear and quadratic term are significant at the 1 percent level. The relationship peaks around 71 centimeters, or 28 inches. If precipitation is cut by one-third, from the optimum 28 inches to 19 inches, annual yields are predicted to decline by 4 percent.

The next two variables are for the effects of temperature. The orange line in Chart 2 displays the effect of a 24-hour exposure to various temperatures. Since there are 183 days between April 1 and September 30, the cumulative effect of temperature exposure dwarfs the effect of precipitation. Unlike precipitation, which used a quadratic specification that is symmetric around the optimum, the effect of temperature is highly asymmetric. As a result, I rely on two piecewise linear approximations. The upward slope of the orange line shows that yields increase in temperatures between 50 and 86 degrees Fahrenheit.

This linear increase is captured by the concept of degree days, which measure how much and for how long temperatures exceed a threshold. For example, degree days 50–86 measure how much temperatures exceed the lower threshold of 50 degrees Fahrenheit up to 86 degrees Fahrenheit. A temperature of 60 degrees Fahrenheit would result in 10 degree days, while a temperature of 86 degrees Fahrenheit or above would result in 36 degree days. The regression incorporates the entire distribution of daily temperatures between the minimum and maximum temperature (Snyder 1985). These daily outcomes are summed over the 183-day April to September growing season to yield one

Chart 2
Relationship between Temperature, Precipitation, Ozone Pollution, and Corn Yields



Note: Shaded areas denote 95 percent confidence bands.
Sources: USDA NASS, NOAA, and author's calculations.

variable—the annual total of degree days between 50 and 86 degrees Fahrenheit. While the annual total omits the sequencing of temperatures within the months, it has been shown to work well as a predictor of yields. For example, corn varieties are often classified by the degree days they need to mature.

The second temperature variable measures degree days above 86 degrees Fahrenheit. Chart 2 shows a highly asymmetric relationship: degree days above 86 degrees Fahrenheit are highly detrimental for corn yields. The downward slope of the orange line above 86 degrees Fahrenheit is an order of magnitude steeper than the increasing slope below 86 degrees Fahrenheit. For example, each 10 additional degree days above 86 degrees Fahrenheit (one day at 96 degrees Fahrenheit rather than 86 degrees Fahrenheit or 10 days at 87 degrees Fahrenheit rather than 86 degrees Fahrenheit) reduces annual corn yields by 2.9 percent. On the other hand, 10 additional degree days between 50 and 86 degrees Fahrenheit only increase corn yields by 0.1 percent.

The ideal weather outcome would be to have a temperature of 86 degrees Fahrenheit throughout the growing season, which is not feasible given temperature fluctuations throughout the year. However, the yield penalty of being above the 86 degrees Fahrenheit threshold is much larger than the penalty of falling below it. This asymmetric penalty again illustrates why a spatially and temporally disaggregated analysis is crucial. A day with a constant temperature of 86 degrees Fahrenheit has the same average temperature as a day with a minimum temperature of 72 degrees Fahrenheit and a maximum temperature of 100 degrees Fahrenheit; however, the latter would have a much greater effect on yields, as half of the day is spent in a temperature range that is highly harmful to yields.

Extreme heat—as measured by degree days above 86 degrees Fahrenheit—is the single best predictor of year-to-year fluctuations in aggregate corn yields (Schlenker and Roberts 2008).[2] A reasonable question is whether modern varieties of corn are less susceptible to extreme heat episodes. The year 2012 was one of the hottest on record (only surpassed by 1988 and the Dust Bowl years in the 1930s), with 101 degree days above 86 degrees Fahrenheit when weather is averaged over the corn-growing area in the United States. However, yields did not fare any better than in previous years of extreme heat. Yields dropped sharply in 2012 (see Chart 1), and the drop even slightly exceeded the estimate from the statistical model using data from 1950 to 2011 (D'Agostino and Schlenker 2016). In other words, there is no evidence that corn varieties have gotten better at withstanding extreme heat in the last decade.

The fifth environmental variable measures exposure to ozone pollution above 70 ppb. Ozone pollution has a strong threshold effect: that is, it has a very limited effect below a threshold, but reduces corn yields linearly above it (Boone, Schlenker, and Siikamäki 2019). The threshold of 70 ppb used in this paper is motivated by the U.S. ambient air quality standard of 70 ppb. Although this threshold differs slightly from the one used by Boone, Schlenker, and Siikamäki (2019), the results are very similar. The ozone standard in the United States is derived in a two-step process: first, by calculating the highest average ozone value for any consecutive eight-hour period for each day—for example, 11 a.m. to 7 p.m. on July 23—and second, by comparing the fourth-highest of these daily maximums to the threshold of 70 ppb. If the fourth-highest of the daily maximums exceeds 70 ppb, a county is deemed in nonattainment. While this is a fairly complex summary statistic, the standard is certainly met if every hourly observation is below 70 ppb. Ozone exposure above 70 ppb adds how much each hourly ozone reading is above 70 ppb, summed over all hourly readings between April and September. The concept is the same as for degree days discussed above. The green line in Chart 2 shows the resulting point estimate. Exposure to 840 ppb-hours (24 hours at 105 ppb rather than 70 ppb—that is, 24 × 35) reduces annual corn yields by 5 percent. Peak ozone pollution in the United States repeatedly exceeded 3,300 ppb-hours in the 1980s, which reduced annual corn yields by 20 percent. Eliminating this peak pollution level has strong effects on yield and productivity trends.

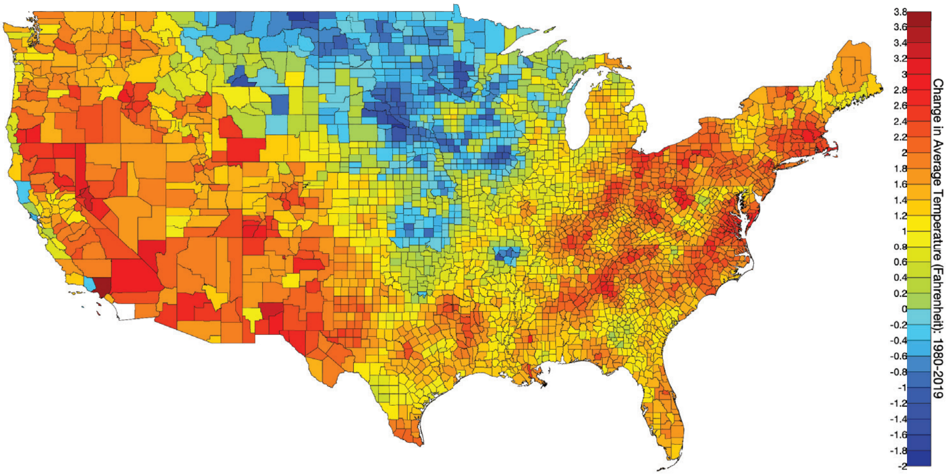
This section has empirically linked five environmental variables to county-level corn yields for the last 40 years. While precipitation has some effect on yields, extreme heat and ozone pollution have led to the largest yield reductions—in some years, more than 20 percent. The next section examines in further detail how these variables have been trending and how they are predicted to trend over the rest of the century.

II. Recent Trends in Peak Temperatures and Ozone Pollution

Temperatures in the United States have been trending mostly upward since 1980, but there is strong spatial heterogeneity even within states (Burke and Emerick 2016). Since 2001, the Chicago Mercantile Exchange has offered weather derivatives, whose payout directly depends on daily average temperatures at eight U.S. airports. The price of these derivatives has been trending upward in close alignment with climate model projections made under the fifth phase of the Coupled Model Intercomparison Project (CMIP5) (Schlenker and Taylor, forthcoming).

The maps that follow present trends over the areas and months in which corn is grown. Specifically, the maps are constructed by using the same weather data set on a 2.5 x 2.5 mile grid for the contiguous United States for the April–September growing season and merging it with the average corn growing area in the years 2010–18 from the cropland data layer in Map 1. Map 2 shows the cumulative change in *average* temperature by county from 1980 to 2019, averaged over the corn area in that county. For predominantly agricultural areas such as Iowa, the map displays the county average, while in more marginally agricultural areas such as the Rocky Mountains, the weather is averaged over a very small subset of the county. Areas with an increasing trend in

Map 2
Trends in Average Temperature by County

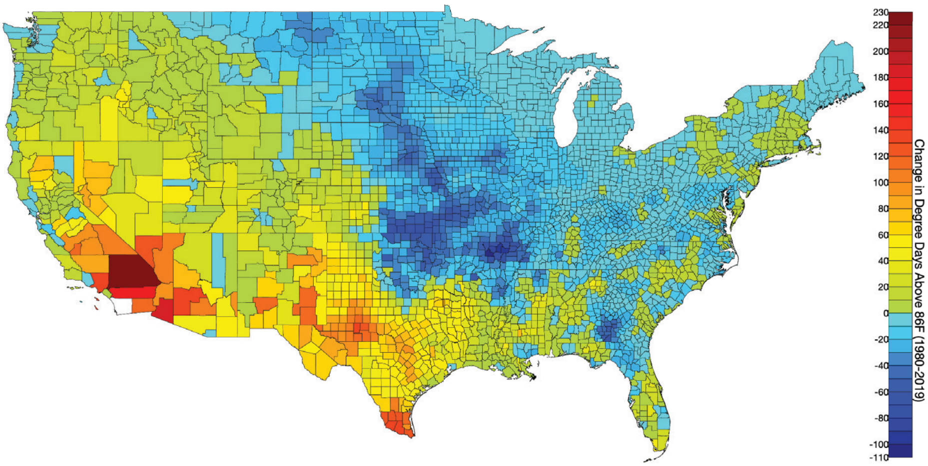


Sources: USDA NASS, NOAA, and author's calculations.

average temperature are shaded green through red, with areas experiencing the largest warming trend in dark red. Areas with a decreasing trend in average temperatures are shaded in blue, with areas experiencing the largest cooling trend in dark blue. The majority of the United States has seen warming, with some areas warming more than 3 degrees Fahrenheit over the 40-year period. However, the northern United States has seen cooling over this period, including South Dakota, some areas in the western edges of the Corn Belt in Nebraska, and some areas in Iowa.

Given the influence of extreme temperatures on agricultural productivity, Map 3 shows trends in the number of degree days above 86 degrees Fahrenheit, again over the average corn area in 2010–19 summed over the April–September growing season. The trends in Map 3 look markedly different from the trends in average temperatures in Map 2. Specifically, areas in the southern Corn Belt and east of the Corn Belt have seen decreases in extremely hot temperatures despite an increase in their average temperatures. One possible explanation for this discrepancy could be an increase in the minimum temperature rather than the maximum temperature during the peak summer months. Another explanation could be an increase in temperatures in the early or late parts of the growing season, when temperatures do not typically

Map 3
Trends in Degree Days above 86 Degrees Fahrenheit by County

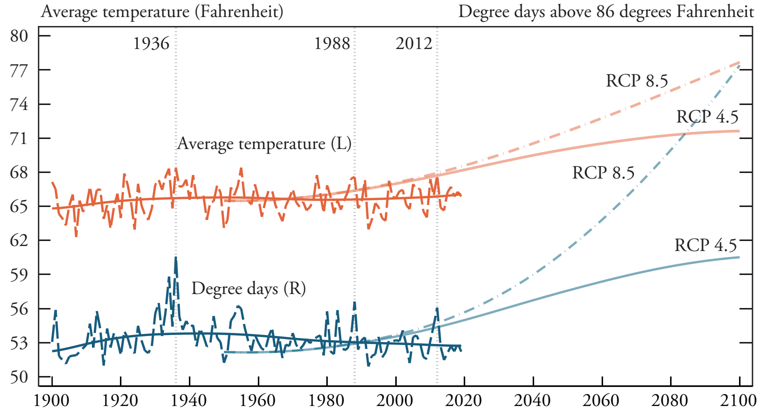


Sources: USDA NASS, NOAA, and author's calculations.

exceed 86 degrees Fahrenheit. However, the cause of this discrepancy is still debated. Some authors have speculated that agricultural intensification has led to a cooling effect on maximum temperatures (Mueller and others 2016). For example, increased irrigation when temperatures spike will increase evapotranspiration, potentially cooling downwind areas. This would suggest a negative feedback loop in which warming leads to counteracting adaptive behaviors on behalf of farmers that limits further warming. This kind of feedback loop is generally not included in climate model forecasts. Although by no means definitive or causal, the close correlation between the corn area in Map 1 and the area experiencing a reduction in extreme heat in Map 3 suggests such a feedback loop may indeed be at play, calling for further study.

Chart 3 constructs observed average temperatures and degree days above 86 degrees Fahrenheit for the entire United States. The orange and blue dashed lines show observed outcomes over time, where the annual average is the average of the county-level outcomes used in the regression in Section I and the weights equal the average corn growing area in each county in 2010–18 in the cropland data layer. As before, the area is fixed and held constant over time, so changes in weather do not reflect changes in where crops are grown. The solid dark blue and

Chart 3
Temperature and Degree Days above 86 Degrees Fahrenheit, 1900–2100



Note: Dashed lines denote year-to-year fluctuations, while solid lines denote trends.
Sources: USDA NASS cropland layer, NOAA NEX-GDDP, and author's calculations.

orange lines show smoothed trends from the locally weighted regression (lowess in STATA).

During the Dust Bowl years in the 1930s, average temperatures and extreme heat (degree days above 86 degrees Fahrenheit) are not necessarily perfectly aligned: the year 1936 saw the most extreme heat, with 177 degree days but an average temperature of only 68.4 degrees Fahrenheit. For comparison, the year 1955 had the same average temperature of 68.4 degrees Fahrenheit but only 100 degree days. Because each additional 10 degree days reduces yields by 2.9 percent, the extra 77 degree days in 1936 imply a further 22 percent reduction in yields relative to 1955. The correlation between the two variables is 0.7. The other years with large exposure to extreme heat, 1988 and 2012, are added as grey dashed lines.

The lighter shade of orange and blue lines on the right-hand side of Chart 3 show the average of climate predictions under the 21 climate models in the NASA Global Daily Downscaled Predictions (GDDP), which provides daily model output for minimum and maximum temperatures on a common 0.5 degree grid that are bias-corrected. Bias correction implies that temperatures in the baseline period (1950–2005) are matched to the observed temperatures over the grid. Because the climate grid is much coarser (half a degree) than the previously used grid (one twenty-fourths of a degree), the two series in Chart 3 do not necessarily have to align perfectly; nevertheless, the average of the trend lines for 1950–2005 is very close. The average temperature in the observed station data in 1950–2005 is 65.5 degrees Fahrenheit, compared with 65.9 degrees Fahrenheit in the NEX-GDDP data.

Comparing the two series reveals one striking difference: the predicted uptick starting in 1980 in both average temperatures and extreme heat has not materialized. While average temperatures over the recent corn growing area and season (orange solid line) are fairly flat with a small uptick at the end, the observed exposure to extreme heat (blue solid line) is actually trending down.

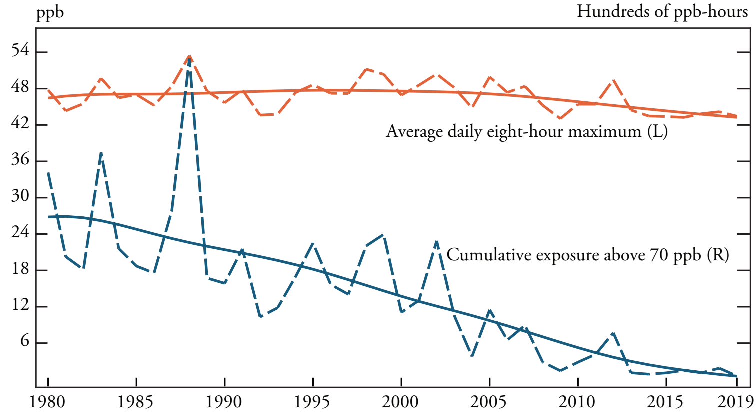
Climate model forecasts in NEX-GDDP use two representative concentration pathways (RCP) scenarios: the RCP 4.5 scenario results in an additional 4.5 Watts per square meter and is considered an intermediate warming scenario, while the RCP 8.5 scenario is considered the worst possible warming scenario. Note that the RCP 8.5 scenario results in the average temperature increasing by 12 degrees Fahrenheit by the end of the century. This is consistent with the Intergovernmental Panel on Climate Change (IPCC) figure of a global average warming of 3.7 degrees Celsius by the end of the century. Average U.S. warming in the RCP 8.5 scenario appears to exceed this global average for two reasons: first, due to the conversion from Celsius to Fahrenheit (times 1.8); and second, because higher latitudes warm more than lower latitudes (another factor of roughly 1.8). Extreme heat, as measured by degree days above 86 degrees Fahrenheit, is predicted to increase sharply from fewer than 50 degree days per growing season before 1980 to more than 450 per growing season by the end of the twenty-first century. This eclipses by far the worst extreme heat the United States has historically seen—the 177 degree days in 1936 when land was abandoned during the Dust Bowl.

This prediction also cautions against the assumption that the cooling effect of agricultural intensification will offset extreme heat in the future. While this cooling mechanism is still debated in the literature, assume for now that it has been at work over the last four decades. If the RCP 8.5 scenario materializes, the implied warming would be so large that land would be abandoned and any offsetting effect would cease, leading to a reversal to the predicted trend line. A similar mechanism was at work when people discussed the "warming hiatus" or "global warming plateau" in the early 2000s. Such decadal phenomena can be linked to ocean circulations that have strong influences on decadal weather patterns. The increasing trend in temperature due to increasing CO_2 concentrations is offset by a decadal weather pattern in the opposite direction—that is, a phase of cooling. However, once the decadal weather pattern reverses its phase from cool to hot and both trends align, the hiatus is followed by a phase of accelerated warming, as was observed in the latter half of the 2010s. In other words, agricultural intensification might lead to a negative feedback loop that temporarily limits the upward trend of maximum temperatures; however, under continued warming that makes the large-scale production of a basic commodity like corn unproductive, the eventual reduction in growing area would lead to a reversion to the trend line.

The right-hand side of Chart 3 also shows the effects of various policy choices. Under the less-severe RCP 4.5 scenario, average temperatures are only predicted to increase by half as much (roughly 6 degrees Fahrenheit) as under the RCP 8.5 scenario, and extreme heat is predicted to increase by about 39 percent by the end of the century. Extreme heat would on average equal the worst observation on record from 1936, which is still sizable: an increase of 120 degree days compared with the historic average from 1900 to 2019. The associated decline in yields would be 35 percent. Granted, if agricultural intensification limits the increase in extreme heat, some of this yield decline may not materialize. Nonetheless, warming trends are predicted to be a major drag on future productivity growth in the United States.

Chart 4 displays the evolution of ozone pollution over the last four decades. The orange line shows average pollution based on the daily maximum eight-hour average concentration—that is, the consecutive eight-hour period with the largest average pollution among the hourly pollution readings. Although the EPA standard is based on the fourth highest daily value, averaged over three years, the graph shows the average of the daily eight-hour maximum concentrations to better reflect the average pollution level during the April 1–September 30 growing season. Peak ozone concentrations are shown in blue by the cumulative exposure to ozone above 70 ppb—that is, the sum of how much hourly ozone readings exceeded 70 ppb over the growing season. This value is constructed for each 2.5 x 2.5 mile grid and then aggregated over the

Chart 4
Average and Peak Ozone 1980–2019



Note: Dashed lines denote year-to-year fluctuations, while solid lines denote trends.
Sources: USDA NASS cropland layer, NOAA NEX-GDDP, and author's calculations.

United States using the average corn area in each grid cell. The year 1988, which had an especially high number of extremely hot days (see Chart 3), also had very high ozone pollution. Since ozone formation increases with sunlight and temperature, it is important to jointly account for both extreme heat and ozone.

Chart 4 also shows the United States' tremendous success in improving air quality, at least as averaged over the corn growing area. Although average pollution (orange line) decreased by a modest 10 percent from 1980 to 2019, almost all peak ozone pollution (blue line) was eliminated. Under a threshold model, which was empirically validated for corn, eliminating peak pollution is all that matters.[3] Log yields, as shown in Chart 1, increased by 46 log points from 4.62 in 1980 to 5.08 in 2019. At the same time, ozone decreased from 2,680 ppb-hours in 1980 to effectively zero in 2019. Without peak ozone pollution, yields in 1980 would have been 15 log points higher. About one-third of the increase in corn yields from 1980 to 2019 is attributable to the elimination of peak ozone. However, now that peak ozone has been driven down to zero, no future yield boost is possible from further reductions in ozone, putting another damper on future yield growth and, accordingly, productivity growth.

III. Socioeconomic Spillovers from Changes in Environmental Productivity Drivers

The previous sections highlighted the importance of two environmental inputs for corn yields: extreme heat and peak ozone pollution. The former is predicted to increase significantly over the remainder of the twenty-first century, while the latter has been reduced to almost zero with no scope for further reductions to boost yields. Taken together, the outlook suggests reduced yield growth in the future. While this article has focused on corn yields, temperature extremes are also important for other crops, such as soybeans, cotton, rice, and wheat (Schlenker and Roberts 2008; Welch and others 2010; Tack, Barkley, and Nalley 2015). In general, agricultural productivity in the United States is likely to decrease under climate change.

The productivity of agricultural workers is also negatively affected by both heat and pollution. Graff Zivin and Neidell (2012) show that picking rates decrease with ozone pollution and temperature. In a competitive market equilibrium, farm workers should be paid their marginal product. If environmental factors reduce overall productivity, wages in the agricultural sector will decline, as will the return to capital. If environmental factors affect the marginal product of capital and labor differently, there will be substitution toward inputs that are less negatively (or more positively) affected. Production of commodity crops in the United States is already highly mechanized, unlike specialty crops, such as fruits, which often need to be picked manually.

The first effect of reduced agricultural productivity due to climate change will be on adaptation measures, which will increase capital investments, especially in new irrigation equipment. Haqiqi and others (2020) add a measure of soil moisture to the statistical model of Section I. Soil moisture is a dynamic state variable that depends on precipitation and evapotranspiration requirements from previous days. Once soil moisture is included in the regression, precipitation becomes insignificant, as soil moisture now captures the effect of water availability. Moreover, the breakpoint that separates yield-enhancing moderate degree days and damaging extreme degree days (86 degrees Fahrenheit in the preceding analysis) depends on soil moisture. The model can be used to derive the value of irrigation, which reduces the yield penalty when soil moisture is low or the breakpoint becomes lower. Because the value of irrigation increases with warming, irrigation is likely to increase, subject to water availability. As noted in Section II, there might be even a positive feedback loop in which further irrigation will limit the increase in extreme heat, at least initially.

The second effect of reduced agricultural productivity due to climate change will be on migration. In the past, negative productivity shocks have operated through both a change in overall productivity and in labor-specific productivity shocks. The 1930s provide a salient example. The years 1934 and 1936 were especially hot, with 1936 holding the record for extreme heat observed over the corn-growing area in the United States to date. Such hot temperatures usually go hand-in-hand with dry conditions, as wet soil would leave to evaporative cooling that limits exposure to extreme heat. Hornbeck (2012) compares changes in land values in eroded versus non-eroded counties following the Dust Bowl in the 1930s. He finds that both revenue and land values persistently declined in more eroded counties. Comparing the immediate decline in revenues, which persisted, to the immediate decline in land values implies that less than one-quarter of the initial difference in agricultural cost could be recovered in more eroded counties through adaptive measures. The main adjustment mechanism was outmigration, primarily of young people, from affected areas as overall productivity declined. Again, recall that climate change is predicted to make the historic record the new normal: the average amount of extreme heat will equal the historic record under the immediate warming scenario RCP 4.5 and almost triple under the fast warming scenario RCP 8.5. Hornbeck and Naidu (2014) provide another example of migration in response to environmental conditions. After the great Mississippi River flood of 1927, flooded areas saw an immediate outmigration of black farm workers that persisted. Although landowners tried to restrict this outmigration, as they benefited from the labor-intensive agriculture, they were forced to substitute labor for capital. This substitution implied that flooded areas saw an increase in modernization compared with non-flooded areas. Both Hornbeck (2012) and Hornbeck and Naidu (2014) examine environmental shocks a century ago. Will the current system be more prone to withstand shocks?

This leads to the third predicted effect of reduced agricultural productivity due to climate change: sectoral reallocation. Other countries have seen such reallocation in the recent past. For example, Colmer (forthcoming) uses micro-level data from India to show that temperature-driven reductions in demand for agricultural labor result in workers looking for new employment opportunities in nonagricultural sectors—specifically, the manufacturing sector. This form of adaptation is important, as labor moves to other sectors that offer higher pay. Colmer estimates that without labor reallocation, the economic cost from reduced agricultural labor demand would be 69 percent higher. In the context of the United States, a natural question is whether labor reallocation is possible within the same geographic area, or whether people will migrate to other areas to seek new opportunities. The migration literature emphasizes that two countervailing effects are usually at work. First, the decision to migrate increases along with the wage differential between the destination and home area. If the home area suffers a negative shock, more people are predicted to migrate as the difference increases. Feng, Krueger, and Oppenheimer (2010) find that weather-induced yield shocks in Mexico influence migration patterns to the United States. When yields in a given area are below average, outmigration is above average, confirming that a deterioration in conditions at home increases outmigration. Second, workers often have to overcome considerable obstacles to migrate, such as cost, lost social networks, or legal constraints in international migration. Especially poor workers might not be able to overcome these costs. If the home area suffers a negative shock, fewer people are predicted to migrate, as the number of people for whom the migration cost is binding increases. This mechanism was also observed in Mexico: when Progressa, a large conditional cash transfer program, made people richer, outmigration to the United States increased (Angelucci 2015).

Movement within the United States is much simpler than across countries, as the migration costs are lower (common language, no legal obstacles). However, even within the United States, some factors limit mobility. Recent decades have seen an increase in urban-rural inequality, only part of which can be explained by the high-skill wage premium (Diamond 2016). This inequality coincided with spatial sorting in which high-skill jobs agglomerated in dense urban areas that saw a concurrent increase in amenities (reduction in pollution and crime, greater access to restaurants and museums). As a result, wages and living costs in urban areas have been increasing drastically, making rural-to-urban migration more costly. Moretti (2013) similarly emphasizes agglomeration effects and discusses why booming tech hubs attract new talent despite extremely high living expenses in these areas. Whether the recent COVID-19 pandemic will reduce some of the amenity premium of cities is an open question as of this writing. In a different context, Walker (2013) examines the effect of environmental regulation on workers' wages and finds that stricter regulation reduced wages more for workers who stayed in the same county and switched to a different sector than for workers who moved to a different county but stayed in the same sector. This suggests that workers are willing to accept a lower wage to stay in their home area, a sign of the cost of migration.

Productivity shocks within the United States could accelerate recent rural-to-urban migration patterns, with implications for rural infrastructure (such as schools), especially if it is primarily younger people who leave. Feng, Oppenheimer, and Schlenker (2012) link shocks to U.S. county-level corn yields over five-year periods to outmigration rates and find that if yields are lower than average, outmigration increases significantly for rural counties with 100,000 or fewer inhabitants—the vast majority of U.S. counties. The semi-elasticity is –0.2, which means a 20 percent reduction in yields would lead 4 percent of the county's population to migrate elsewhere. Where exactly these people are going is subject to ongoing research. The Internal Revenue Service (IRS) has made available migration data based on the address where a W-2 was filed—these data may help answer the question of whether people who leave a rural county go to other rural areas or urban areas either within the same state or another state.

The fourth predicted effect of reduced agricultural productivity due to climate change is general equilibrium price feedback. This is an issue that is generally not addressed in partial-equilibrium empirical studies that assume all other factors remain fixed. Most studies rely on county-level yield shocks in a one or five-year period. Some counties experience lower-than-average yields in a given year, while others see above-average yields. In contrast, climate change is predicted to decrease yields in all U.S. counties as temperatures increase. Prices will adjust accordingly.

The United States is the major producer of basic calories, with four staple crops: corn, wheat, rice, and soybeans. Together, these crops account for 75 percent of all calories that humans consume, either directly or indirectly through their use as feed for livestock. The U.S. share in this market has been around one-quarter, much larger than Saudi Arabia's share in the global oil market (Roberts and Schlenker 2013). Anything that influences U.S. yields will also have a strong influence on global agricultural markets. If climate change were to reduce U.S. agricultural productivity, global commodity prices would increase. These price increases would offset some of the productivity losses farmers are predicted to incur. Given the highly inelastic supply elasticity of 0.11 and demand elasticity of –0.05 in Roberts and Schlenker (2013), the required price increase to balance global supply and demand would be substantial. Climate change would, in effect, do what the U.S. government has tried to for decades: limit supply to drive up the price of agricultural commodities.

The general equilibrium effect, therefore, is more refined than the partial equilibrium effect. Farmland in currently hot areas will become so unproductive that it will be abandoned, similar to what was seen during the Dust Bowl. On the other hand, farmland in moderate climates, such as the northern edge of the United States and Canada, will see an increase in farmland values as lower productivity is more than offset by an increase in prices. The result is a regional reshuffling of the growing area. Although a price increase will benefit producers, it will of course hurt consumers who have to pay more to meet their dietary needs. There are additional caveats to this prediction, as global food prices will further depend on what happens to yields in the rest of the world—for example, whether the rest of the world will also suffer a loss in productivity due to climate change, or whether Africa will be able to reduce its yield gap (that is, increase yields to levels that should be feasible due to its climate).

IV. Conclusions

This article emphasizes the importance of two environmental factors that are crucial inputs into the agricultural production function: extreme heat and peak ozone pollution. Climate change is predicted to significantly increase the occurrence of extreme heat by the end of the century, although this trend has not materialized over agricultural areas during the last four decades. The success of the Clean Air Act implies that almost all peak ozone pollution above 70 ppb has been eliminated over agricultural areas, and no further yield-enhancing reductions are possible. Taken together, these findings suggest that corn yields, which increased exponentially from 1940 to 1980 but more slowly since, will likely see a further slowing in the growth rate going forward.

Similar projections hold for other commodity crops. While agricultural practices might initially reduce the increase in extreme heat through a negative feedback loop, the projected increase in extreme heat by the end of the century is so large that even under the intermediate warming scenario, the hottest year on record (during the Dust Bowl) will be just an average year. Even the widespread adoption of irrigation will not be able to substantially limit the occurrence of extreme heat through evaporative cooling at this level of warming. Although irrigation will help mitigate the damaging effects of extreme heat on crops, the cost to do so for commodity crops such as corn is very high. A less costly adaptation is moving growing areas north. Northern areas are somewhat protected from a decrease in yields through a likely accompanying offsetting increase in commodity prices, given the dominant market share of U.S. commodities. Finally, the climate-change-related decline in agricultural productivity is also projected to accelerate rural to urban migration, especially from agricultural areas that are already hot to begin with.

Endnotes

[1]Data were downloaded from https://aqs.epa.gov/aqsweb/airdata/download_files.html#Raw

[2]Schlenker and Roberts (2008) find crop-specific break points of 29 degrees Celsius (84.2 degrees Fahrenheit) for corn, 30 degrees Celsius (86 degrees Fahrenheit) for soybeans, and 32 degrees Celsius (89.6 degrees Fahrenheit) for cotton. For simplicity, this paper uses 86 degrees Fahrenheit when discussing all crop yields and for showing trends.

[3]The United States has two ozone standards: a primary standard designed to address human health and a secondary standard for all other factors, including crop yields. As an aside, epidemiological evidence suggests that ozone fluctuations below the 70 ppb standard still influence human health.

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