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The contribution of the University of California Cooperative Extension to California's agricultural production

Diti Chatterjee^a, Ariel Dinar^b and Gloria González-Rivera^c

^aDepartment of Environmental Sciences, University of California, Riverside, CA, USA; ^bSchool of Public Policy, University of California, Riverside, CA, USA; ^cDepartment of Economics, University of California, Riverside, CA, USA

ABSTRACT

Purpose: This paper is concerned with the impact of the University of California Cooperative Extension (UCCE) on regional productivity in California agriculture. UCCE is responsible for agricultural research and development (R&D), and dissemination of agricultural know-how in the state.

Method/methodology/approach: We estimate the effect of UCCE on county-level agricultural productivity for the years 1992–2012, using an agricultural production function with measures of agricultural extension inputs alongside the traditional agricultural production inputs at the county level.

Findings: Results show a positive impact of UCCE through its stock of depreciated expenditures. For an additional dollar spent on UCCE expenditures stock, agricultural productivity, measured as value of sales at the county level, improves by \$1–9 per acre of farmland for knowledge/expenditure depreciation rates between 0 and 20 percent.

Practical implications: Results suggest that county differences in productivity could affect extension expenditures. The high level of contribution found in the results would be especially useful during a period of political pressure to reduce public spending for agricultural extension in the state.

Theoretical implications: Theoretical implications suggest that agricultural systems with higher level of knowledge depreciation are associated with higher resulting incremental agricultural productivity per an additional dollar spent on UCCE expenditures stock. This suggests that extension policy should consider also the agricultural system (crop mix).

Originality: We use original budgetary data that was collected especially for answering our research questions from archives of UCCE. We estimate impact of extension at the county level in California, on the value of agricultural sales (of crops and livestock). We developed an extension expenditure stock, using current and past expenditures data, and different depreciation rates, following the theory of Knowledge Production Function.

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Agricultural productivity; University of California Cooperative Extension; public R&D expenditure; R&D lags; California counties

1. Introduction

The history of American agricultural extension dates back more than 100 years. The Morrill Act of 1862 established land-grant universities across the country with the purpose of educating the citizens about agriculture, home economics, and other practical professions.¹ According to the Act, each state had to set aside acreage of federal land, the income from which would have to support a college or university for teaching ‘mechanical arts’ (Rogers 1988). Twenty-five years later, in 1887, the Hatch Act was passed, which established the allocation of federal funds to state agricultural experiment stations. The Smith-Lever Act of 1914 formalized the cooperative extension through the creation of a partnership between the land-grant research universities and the U.S Department of Agriculture. The Congress clearly stated the purpose of Extension: ‘to aid in diffusing among the people of the U.S. useful and practical information on subjects related to agriculture and home economics, and to encourage the application of the same’ (Rasmussen 1989). Funding for the Cooperative Extension would come from the Congress to the United States Department of Agriculture, which would then distribute it among the land-grant universities, matching the amount to the state- and county-level expenditures.² The formula designed for allocation of funding for Cooperative Extensions mandated that the federal and state contribution would each amount to 40 percent, with county contributions amounting to 20 percent of the total (Rogers 1988). In this paper, we do not distinguish between the 1914 Act and the Hatch Act, as both provide funding for research and dissemination activities within Cooperative Extension.

Previous works in the United States and California suggest high but declining productivity of extension over time, which is explained by reductions in extension expenditures. Alston, Pardey, and James (2009) reported that sustained growth observed in the United States, as well as in California, has been possible due to improvement in total factor productivity, mainly through publicly funded research and development. However, the state of California has experienced a reduction in productivity growth consistently during the last 50 years. United States agriculture in general has been experiencing a decline in growth of productivity, according to Ball, Schimmelpfennig, and Wang (2013). Alston, Pardey, and James (2009; Alston, Pardey, and Chan-King 2013) reported that public funding allocated towards agricultural R&D has been declining over that period in the country and is the primary reason for a decline in productivity growth. However, Jin and Huffman (2016) have been able to define extension expenditures separately from research expenditures, and have successfully estimated separate positive impacts of research and of extension on agricultural productivity in the U.S.

Given the future prospects of the agricultural role in food production and use of natural resources, such as water and land, there is a need to better understand the relationship between public expenditures on R&D and extension, and its impact on productivity in order to assess how budget cutbacks can affect agriculture in the long run. Early studies, including Griliches (1964), estimated an agricultural production function, introducing a research and extension variable along with the conventional input variables. Previous work (Huffman 1974, 1976, 1977, 1981) has focused on the contributions of extension at the county level in Midwestern and Southern states. In particular, these works refer to: North Carolina, South Carolina, Mississippi, Alabama, Illinois, Indiana, Iowa, Minnesota, Ohio, and Oklahoma. Some of these works focus on the role of extension

in allocative efficiency of nitrogen in the production of corn, and some estimate a production function that accounts also for education and extension.

Huffman and Evenson (1993) and Alston, Craig, and Pardey (1998) analyzed in detail the elements that impact total factor productivity (TFP) in U.S. agriculture. The former study covered the period 1950–1982 for 42 U.S. states. They used expenditures on public and private research and agricultural extension to explain TFP. Findings suggest a positive impact of public agricultural research on productivity. Alston, Craig, and Pardey (1998) analyzed an aggregated dataset, including 48 U.S. states for 1949–1991, and examined the impact of a single combined public agricultural research and extension expenditure variable on TFP for the U.S. Their results show a positive impact of the combined public agricultural research and extension expenditure variable. Recent studies, such as Alston et al. (2011), Fuglie and Toole (2014), and Wang et al. (2013) provided evidence that expenditures on agricultural research created new knowledge and technologies, which enabling improvements in agricultural productivity in US agriculture. Alston et al. (2011) reported an own-state payoff of \$33.3 and a national-level payoff of \$43.4 (including California and inter-state spillover) for every dollar spent by California's research and extension system during the period 1949–2002. These most recent studies aggregated extension and publicly funded R&D into one combined variable in their analysis. Jin and Huffman (2016) is one of the few papers that included public expenditures on agricultural research and extension as separate variables for a U.S. state-level analysis for the years 1970–2004. Their results provide evidence of social rates of return exceeding 100 percent for public extension, and 67 percent for publicly funded agricultural research. A recent study (Lampach, Nguyen Van, and Nguyen 2018), using a meta-analysis of 196 crop observations (from 96 recently published studies) showed that extension activities have a significant and positive effect on technical efficiency at specific crops farming systems. Being crop specific, the results suggest interesting differences between types of crops across the entire sample. These findings could be important for policy design in different regions (counties) and crop specification (as was also found in our study).

Extension is often considered a system of dissemination of agricultural knowledge, but it is more than just that. In the case of UCCE, there are about 1,000 advisors located across the various county offices, and researchers at the University of California campuses of Berkeley, Davis, and Riverside. The advisors and researchers are engaged in creation and dissemination of knowledge. The knowledge produced in both basic and applied research is disseminated to farmers and ranchers. While state-level agricultural research, conducted also in the United States Department of Agriculture (USDA) Agricultural Experiment Stations (AES), could be more oriented towards the general goal of productivity enhancement, research and extension work carried out at a local level, such as a county, could be more focused on solving local impediments, which then fuel improvements in local productivity.

We rely on the theory of knowledge production function and apply it (Chatterjee, Dinar, and González-Rivera 2018) to the agricultural extension system of California, a research-based and knowledge creating and disseminating system. The theory (Chatterjee, Dinar, and González-Rivera 2018 and the literature they cite; Griliches 1964; Dinar 1991; Alston et al. 2011) views knowledge as an input to, say, agricultural food production. As such, knowledge is itself an output of a process of its creation. The process of knowledge creation includes inputs such as human resources (researchers, extension specialists,

support staff) and monetary resources for conducting field experiments and their dissemination. All these inputs, including human resources, can be expressed in monetary units (salaries of the researchers, for example). The knowledge produced by research or extension system grows over time as more knowledge is produced and added (to the stock of knowledge), some of which is also subject to depreciation. This means that certain types of knowledge become less relevant or even obsolete after some time. This is called the depreciation of knowledge, exactly as the depreciation of buildings or machines, and need to be replaced. The contribution of an extension system is in its ability to continue producing and replacing knowledge that became less relevant. Due to the local/regional aspects associated with agricultural production, knowledge may face challenges, depending on the region (county).

The main contribution of our paper is in the estimation of the impact of extension at the county level in California, on the value of agricultural sales (of crops and livestock), which we use as an indicator of county-level agricultural productivity (Huffman 1976 and 1981 were the first to analyze extension contribution at the county level in several states other than California).³ To our knowledge, this is the first study with a county focus in California, one of the biggest and diverse agricultural economy in the nation and the world. Our work relies on the theory of knowledge production function and knowledge depreciation. We show how the theory of knowledge production and depreciation can be used to estimate the contribution of a system such as the UCCE, which is dedicated to creating and replacing knowledge, to the economy of the state of California. The results of the analysis would be especially useful during a period of political pressure to reduce public spending for agricultural extension in the state. The county focus of our study is especially useful, as opposed to analyses at state level, which is common to most recent works, because it allows a more targeted policy intervention on higher and lower performing regions (e.g. counties).

Our model includes the expenditures allocated by UCCE towards agricultural R&D and outreach/dissemination activities. The empirical analysis captures the impact of an expenditure stock, under the assumption that old expenditures also impact current productivity. However, the intensity of the impact of past expenditures on current productivity decreases over time. This idea is analogous to that of depreciation of the past, and henceforth has a lesser impact on productivity. To capture this effect, expenditure stock is created using current and past expenditures data, and different depreciation rates are considered⁴ to analyze the impact of UCCE on county-level productivity in California for the period 1992–2012, for which data is available.

The remainder of the paper is organized as follows: Section 2 provides background on the UCCE system and the agricultural sector of California. In Section 3 we outline the econometric methodology used for the analysis. In Section 4, we describe the data and variable creation, and in Section 5, we discuss the empirical results. We end the paper in Section 6 with conclusions and policy implications.

2. Background on UCCE and California agriculture

Through the course of almost a century, the University of California Cooperative Extension (UCCE) has grown into a much more elaborated system, which has branched out from handling mainly farm-related issues to many other aspects concerning the farm as

well as the overall society. Extension advisors communicate practical research-based knowledge to agricultural producers, small business owners, youth, and consumers, who then adopt and adapt it to improve productivity and income. Today the UCCE works in six major areas:⁵ *Agriculture, 4-H Youth Development, Natural Resources, Leadership Development, Family and Consumer Sciences, and Community and Economic Development*. Indeed, each of the six major areas is related to agricultural productivity. However, it is impossible to identify the exact interactions and impacts. The case of natural resources deserves more careful explanation. Unlike Jin and Huffman (2016), who used data for other states on ‘agricultural and natural resource extension,’ UCCE has no combined ‘agriculture and natural resources,’ but only ‘natural resources,’ which is explained in the UC Agriculture and Natural Resources website (<http://ucanr.edu/Environment/>). The activities in UCCE’s ‘natural resources’ program focus not on agricultural aspects but rather on environmental aspects, such as forestry, hardwood rangelands, marine resources, pasture and range, wildfire, wetland ecosystems, and other environmental amenities, including water for nature. Based on the spread of issues addressed, we decided not to use extension programs and activities under the ‘natural resources’ program in this paper. Instead, we focus on the role of UCCE in agriculture, hence analyzing data related only to the agricultural component of UCCE activities. We refer to UCCE expenditures as the budgetary expenses related to agricultural R&D and outreach/dissemination.

California ranks first among the top five U.S. agricultural producers, according to the *California Statistical Review 2014–2015*, with crop cash receipts at \$53.5 billion (13 percent of the nation’s total). The state’s agricultural abundance includes more than 400 varieties of agricultural products. It produces nearly half of the nation’s vegetable produce, and leads the nation in the production of fruit and nuts, such as almonds, walnuts, dates, figs, grapes, and plums. UCCE has been in operation in California for the past 100 years, and has contributed significantly to enhancing productivity, making the state a leader in agricultural production and income generation. According to a report by University of California Division of Agricultural and Natural Resources,⁶ UCCE has made considerable contributions to California’s agriculture. These include: development of salinity management practices that helped turn the arid soils in the Central Valley into one of the world’s most productive regions; and advancements in irrigation, planting and pruning that raised almond yields, and broccoli production. UCCE has developed as many as 40 different varieties of citrus; established strawberry varieties that are now produced in the state and constitute 40 percent of the nation’s production; helped to create a \$119 million artisan cheese-making industry in Marin and Sonoma counties; assisted California growers in saving \$65 million in water costs and reduced irrigation water usage by 100,000 acre-feet due to the irrigation scheduling services provided by the California Irrigation Management Information System (CIMIS); reduced urban landscape runoff and pesticide use in the state, thanks to the Master Gardener program and the Integrated Pest Management System (IPM).

3. Methods and empirical specifications

Our empirical estimation of the impact of extension expenses on agricultural productivity uses a production function model with agricultural productivity as the output, as well as

various market and non-market factors, including research and extension expenditures as the inputs. Griliches (1964), Evenson (1978), Alston, Craig, and Pardey (1998, 2011), and Jin and Huffman (2016) estimated an agricultural production function model with research and extension inputs. All except Griliches (1964) estimated the agricultural production function, including total factor productivity as their dependent variable, which is the net productivity growth after subtracting the effect of inputs such as labor, land, machinery, and chemicals on agricultural output. These studies used non-market inputs of production and expenditure stocks in their econometric analyses. Griliches (1964) estimated a Cobb–Douglas production function, controlling for land, labor, machinery, chemicals, and farmer education. We follow the literature and estimate several forms of the production function, which include Cobb–Douglas, quadratic, and linear forms.

3.1. The modeling framework

The studies we reviewed in Section 2 assume that the R&D expenditures' impact on productivity is dynamic. This implies that at any given period in time, productivity is impacted by a cumulative stock of past and present expenditures, sometimes referred to as the 'knowledge stock' (Alston, Craig, and Pardey 1998; Chatterjee, Dinar, and González-Rivera 2018). The theory is derived from the idea that current research (extension)-based knowledge is an accumulation of past and present knowledge; some of the old knowledge depreciates over time and becomes less effective, meaning that technologies and management practices become obsolete.

With such background, the agricultural output is a function of traditional inputs and agricultural knowledge stock produced through a stream of expenditures on R&D and outreach (in our case – extension expenditures such as advisors, experiments, and outreach/dissemination activities).

$$Q_{it} = g(K_{it}, FP_{it}, C_{it}, u_{it}) \quad (1)$$

where i = county, t = year, K represents stock of knowledge, FP represents traditional factors of production, C represent other control variables, such as farmer characteristics, and u represents the unknown factors.

The stock of knowledge can be represented as a function of the stream of current and past R&D expenditures:

$$K_{it} = f(E_{it}, E_{i,t-1}, E_{i,t-2}, E_{i,t-3}, \dots, E_{i,t-n}) \quad (2)$$

where E denotes expenditures by UCCE, and n denotes total number of time lags used for depreciation of the knowledge.

The corresponding econometric model we estimate is

$$y_{it} = \alpha + \beta_1 K_{it} + \beta_2 L_{it} + \beta_3 HL_{it} + \beta_4 M_{it} + \beta_5 C_{it} + \beta_6 PO_{it} + \beta_7 A_{it} + \rho S_i + \theta F_t + \varepsilon_{it} \quad (3)$$

where $i = 1, 2, \dots, 50$; $t = 1992, 1997, 2002, 2007, 2012$. y is the total value of sales of agricultural products per acre of farmland (of crops and livestock), K is the stock of knowledge, L is acres harvested, HL is hired labor,⁷ M is machinery, C is acres on which chemicals are applied, PO is number of primary-occupation farmers, A is average age

of farmer, S is the county fixed effects variable, F is the year fixed effects variable, and ε is the error term.

All the variables listed above are expressed in terms of per acre of farmland in a county, to reduce bias due to size of large versus small counties. There are differences in size among the various counties in California. Some counties are very big and very active, and others are very small and less active in terms of agricultural production. To compare counties that differ in size, we refer to their per acre values. In addition, we introduce county fixed effects that consider idiosyncrasies of the counties that have not been captured by the other variables. This approach has been used in the literature in earlier works (e.g. Alston, Craig, and Pardey 1998).⁸

The above model assumes that UCCE expenditures on R&D and outreach are allocated towards research that minimizes the impact of climatic variables, such as county-level temperature and precipitation variability on productivity.⁹

The variable for knowledge stock enters our model as a sum of current expenditures and a depreciated sum of last period's extension expenditures stock:

$$K_{it} = E_{it} + (1 - \delta)K_{it-1} \quad (4)$$

In Equation (4), δ is the rate of depreciation of the stock of existing knowledge. Alston, Craig, and Pardey (1998) and Griliches (1998) observed that some knowledge produced through research and development process depreciate through time and finally becomes obsolete. The rate of depreciation has varied for different studies. Griliches (1980, 1986) implemented knowledge depreciation rates of 0, 10, 15, and 20 percent. Adams (1990) estimated an annual depreciation rate of 9–13 percent. Khan and Salim (2015) set a depreciation rate for R&D at 8 percent in their study. In this paper, we estimated models (3) and (4) for depreciation rates ranging from 0 to 20 percent, and higher, using the entire range of depreciation rate that has been suggested in previous work. This range of δ could represent different types of agricultural systems that are characterized by different rates of knowledge duration cycles.

Pardey and Craig (1989) concluded that at least 30 years of lagged variables may be optimal and may capture the impact of research on agricultural output. Alston, Pardey, and Ruttan (2008) and Alston et al. (2011) tested 30- and 50-year lags of research expenditures, respectively. Jin and Huffman (2016) used 35-year lags of public agricultural research expenditures and four-year lags for public agricultural extension in their empirical analysis. For our study, we include five lagged values of UCCE expenditures in our construction of knowledge stock, which is calculated using the following equation:¹⁰

$$K_{it} = E_{it} + (1 - \delta)E_{it-1} + (1 - \delta)^2E_{it-2} + (1 - \delta)^3E_{it-3} + (1 - \delta)^4E_{it-4} + (1 - \delta)^5K_{it-5} \quad (5)$$

One may suggest the existence of endogeneity in the allocation of UCCE budgets. However, through interviews of UCCE officials (county directors) regarding the budget allocation process and UCCE knowledge production (Chatterjee, Dinar, and González-Rivera 2018, Appendix Table A4), we were provided information that led us to reject that hypothesis. The interviews revealed that county-level UCCE budgets are allocated depending on the overall state and federal funds allocated to that particular county, as

well as the negotiations between UCCE county directors and the county government's board of directors. This makes the process of allocation of funds towards UCCE activities exogenous and, to a large extent, independent of the level of productivity of the county's agricultural sector. Furthermore, as suggested by Guttman (1978), Rose-Ackerman and Evenson (1985), Pardey (1989), and Pardey and Craig (1989) political rather than economic efficiency criteria influences the allocation of public agricultural research and extension resources.

4. Data

Our two main data sources are the agricultural census that provides 5-year waves of data, and the annual UCCE budget. Both datasets provide data at the county level. Below we explain the features of both data sources.

4.1. Agricultural production data

We use agricultural census data for the years 1992, 1997, 2002, 2007, and 2012 for the information on the value of agricultural sales, quantities of major inputs applied, and farmer characteristics. The agricultural census survey is conducted by the U.S. Department of Agriculture (USDA) across the nation every five years. The data we use is aggregated at the county level for each county in California. All monetary values used in the paper are expressed in constant 2013 USD.

California has 58 counties in total. We collected UCCE expenditure budget data by county offices for the years 1992 through 2012. Some counties in California have a shared budget allocation with another county; such counties include Humboldt and Del Norte, Inyo and Mono, Placer and Nevada, Plumas and Sierra, Sutter and Yuba, Shasta and Trinity, and San Mateo and San Francisco. We consider each of these two-county combinations as a single county for our analysis. There is no UCCE office in the county of Alpine in our records, so it is excluded from the analysis. We use the entire set of 50 counties, and we refer to UCCE budget data as extension expenditures.

For our empirical model, 'Land' is measured as total harvested acres. 'Labor' is represented by total number of hired labor employed. 'Machinery' is the sum of all kinds of machines used in the production process for each county, which includes cotton pickers and strippers, forage harvesters, grain and bean combines, hay balers, tractors, and trucks, including pickups.¹¹ The variable 'chemicals' is the ratio of the sum of all acreage on which fertilizers and pesticides were applied, to total farmland. We were constrained by the data in the Farm and Ranch Irrigation Survey (FRIS) regarding several inputs. Use of chemicals was one of them. FRIS reported the acres treated with chemicals, and this was our only source for input of chemicals. A higher share of farmland acreage that is treated with chemicals is expected to be associated with higher yields and thus higher sale values.¹²

We use the variable 'average farmer age' to represent farmer experience in a county. We also include total number of farmers in a county with farming as their primary occupation as a second farmer characteristic variable.

Summary statistics for the entire data set ($N = 250$, 50 counties over five years – 1992, 1997, 2002, 2007, and 2012) are reported in [Table 1](#). Mean total value of sales per acre for

Table 1. Summary statistics.

Variable	Observations	Mean	S.D.	Minimum	Maximum
Total value of sales per acre of farmland	250	1315.68	1505.09	14.74	10331.21
UCCE expenditures per acre of farmland	250	6.21	8.59	0.64	62.92
Acres harvested per acre of farmland	249	0.25	0.22	0.001	0.93
Hired labor per acre of farmland	250	0.02	0.04	0.0001	0.28
Machinery per acre of farmland	250	0.01	0.01	0.001	0.06
Chemicals (acres) per acre farmland	250	0.64	0.60	0.003	2.14
Primary occupation farmers	250	847.90	807.40	83	4363
Average farmer age	250	57.19	2.25	51.55	63.8

Note: There is one missing observation for harvested acres in the data set; it was published as 'missing,' in the 1992 agricultural census by USDA.

our data is \$1,316, and UCCE expenditures per acre is nearly \$6.¹³ One-fourth of an acre of farmland is harvested on average.¹⁴ One unit of hired labor is employed per 50 acres of farmland, and one unit of machinery is used per 100 acres. Chemicals and fertilizers are applied to nearly two-thirds of farmland acreage.¹⁵ The average farmer's age in the state is 57.2 years.¹⁶

Figure 1 shows the relationship between total value of sales per acre and the stock of extension expenditures per acre for each year for all counties. We observe a positive correlation of 0.81, 0.66, 0.70, 0.53, and 0.25 between extension expenditures and productivity (sales) for the years 1992, 1997, 2002, 2007, and 2012, respectively. We also observe very high levels of extension expenditures for counties such as Los Angeles and San Francisco-San Mateo. Los Angeles county agricultural products include alfalfa, one of the most important crops in that region. Its average total value of sales per acre is \$2,547, which is nearly double the sample mean of \$1,316. Mean extension expenditures per acre for the county equals \$30, which is nearly five times the sample mean of \$6.2. San Francisco-San Mateo counties include wine and apiary products as their most prominent crops. These two counties have the highest mean extension expenditures per acre of \$45, and a mean total value of sales per acre of \$3,283.

Santa Cruz has the highest average value of sales per acre among all counties, which equals \$6,902, and its mean extension expenditure per acre is \$24. The highest amount of cash receipts for the county comes from strawberries, raspberries, and other berries, followed by nursery crops and vegetables like Brussels sprouts and lettuce. Mariposa has the lowest average value of sales per acre at \$53, and \$2 worth of average UCCE expenditures per acre. It can be argued that higher expenditures on research and extension in some of the lower-performing counties can be substitutes for other traditional inputs, which may be scarce in supply. With the availability of efficient methods of agriculture, higher income for farmers as well as lower-priced, home-grown crop production can be ensured for the county, thereby benefitting both the consumers and producers of agricultural products. Section 5.3 of the paper discusses the issue of substitutability of traditional inputs with extension expenditures for policy purposes.

4.2. UCCE budget data

The annual UCCE budget data includes different expenditures, such as salaries, infrastructure, dissemination, and experiments cost. We roughly aggregate the expenditures into two groups: salaries and infrastructure (that includes all the rest). UCCE total annual

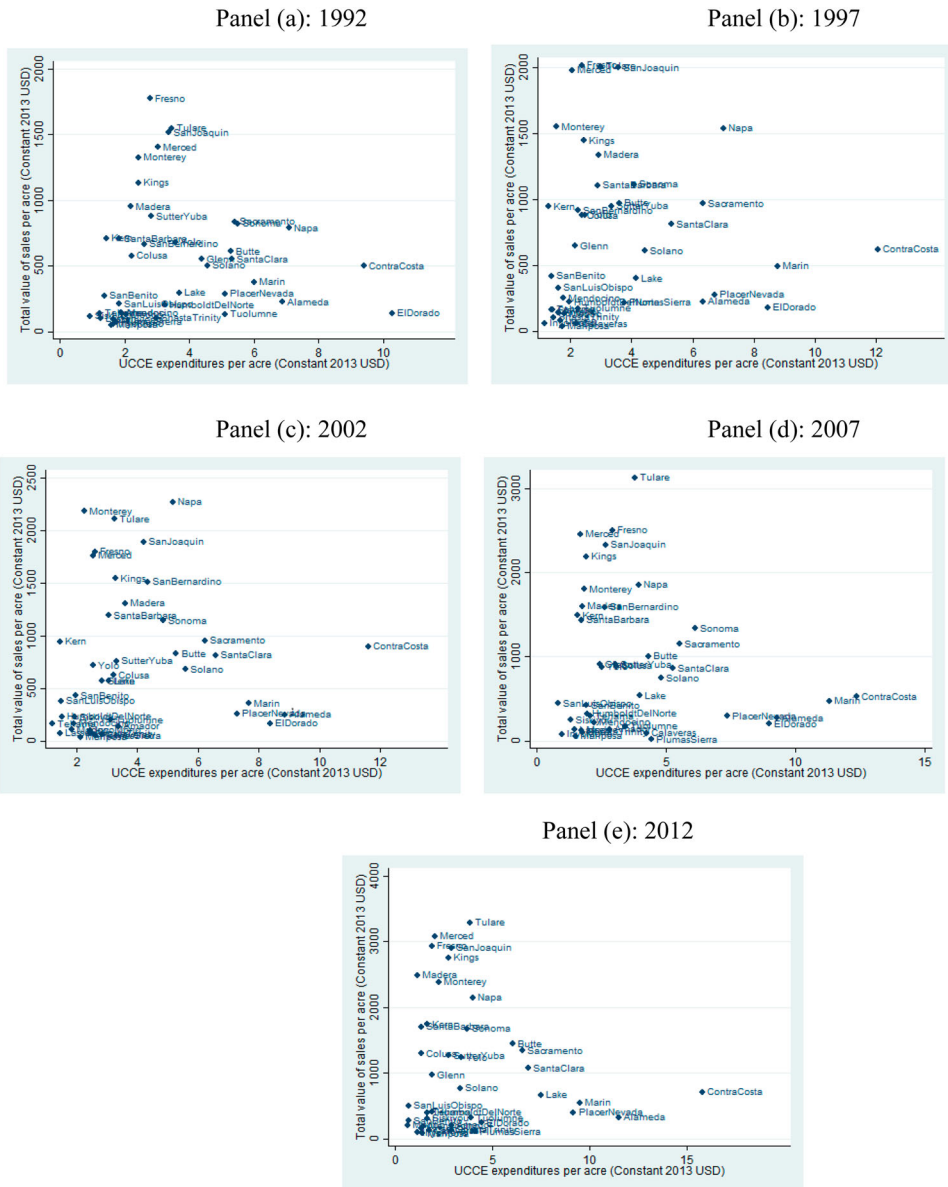


Figure 1. County-level total value of sales per acre vs. UCCE expenditures per acre (constant 2013 USD) for 1992–2012.³⁰

expenditures range between \$77 and \$90 million (of which salary expenses range between 17 and 22 percent). State-level expenditures (in constant 2013 USD) by UCCE trended lower in the 1990s as can be seen in Figure 2, Panel (a). This trend was broken in the early and mid-2000s but, around the 2008 financial crisis, UCCE expenditures experienced further decline to reach the lowest level since 1992. In Figure 2, Panel (b), we can see that the total value of sales per acre of farmland in California has been growing over the five census years included in our analysis. Between the period of 1992 and 2012, the total value of agricultural sales per acre of farmland has risen (from \$889 to \$1,693) by 90

percent. Real expenditures made by UCCE normalized per acre have remained relatively unchanged over these census years, ranging between \$3.1 and \$3.6.

Over the same period, we observe a 12 percent reduction in acres of farmland in the state, declining from 29 million acres in 1992 to 25.5 million in 2012.

When we consider the stock of extension expenditures instead of the extension expenditures for the current year only, then the picture is different. In [Figure 2 Panel \(c\)](#), we observe that the stock of extension expenditures (sum of current and five previous year's expenditures) per acre has remained more or less stable around \$20 per acre in 1997 and 2002, and has risen slightly in 2007 and 2012. The value for 1992 is \$3.4, which is about 20 percent of the mean for the rest of the period. The reason for this difference is the fact that we did not have data for UCCE expenditures in the five years prior to 1992. For the year 1992, aggregate state level data for five lagged values of UCCE expenditures were available. Upon computing the expenditure stock at the state level, using [Equation \(5\)](#), we observed that expenditures stock remained comparable to the four other census years. We used this result to assume that UCCE expenditures stock for each county remained comparable across the 5 census years. Making use of this assumption, we have inflated UCCE expenditure of 1992 for each county by a multiple of 5 in our empirical analyses. Our general observation is that even though the annual UCCE expenditures have fallen over time, the extension expenditure stock per acre of farmland has risen slightly over this period. We observe a decline in the extension expenditure stock in 2012; this may be the reflection of the effect of the steady decline in annual UCCE expenditures since 2009 that we observe in [Figure 2 Panel \(a\)](#). We observe also in [Figure 2 Panel \(b\)](#), a positive relationship between this cumulative input and sales per acre over the period of our study.

Some of the funding for extension activities is statewide funding that should be included in the analysis. However, our experience with statewide funding of extension activities is such that we decided not to include it in our analysis. State funding (beyond programs that we discussed earlier in the paper) for extension activities is ad-hoc and is the result of catastrophic events, such as flooding, diseases, and other local or regional (or even statewide) disasters. Therefore, such funding is hard to find in one source, and its attributes could be different from year to year. We decided not to use this type of funding in the analysis. Our decision could lead to over-estimation of the contribution of budget dollars that are provided for extension.

5. Results and discussion

We estimated several functional forms of the production function model, including Cobb–Douglas, quadratic (in some variables), and linear. However, the coefficients in both the quadratic and the Cobb–Douglas functional forms did not behave as expected, and many of them were not significant. Therefore, we report the results of only the linear functional forms.

5.1. Mean county-level impact of UCCE

Empirical results for the county-level panel data analysis from [Section 3](#) are reported in [Table 2](#). We have considered a number of cases. In the first case, we considered knowledge

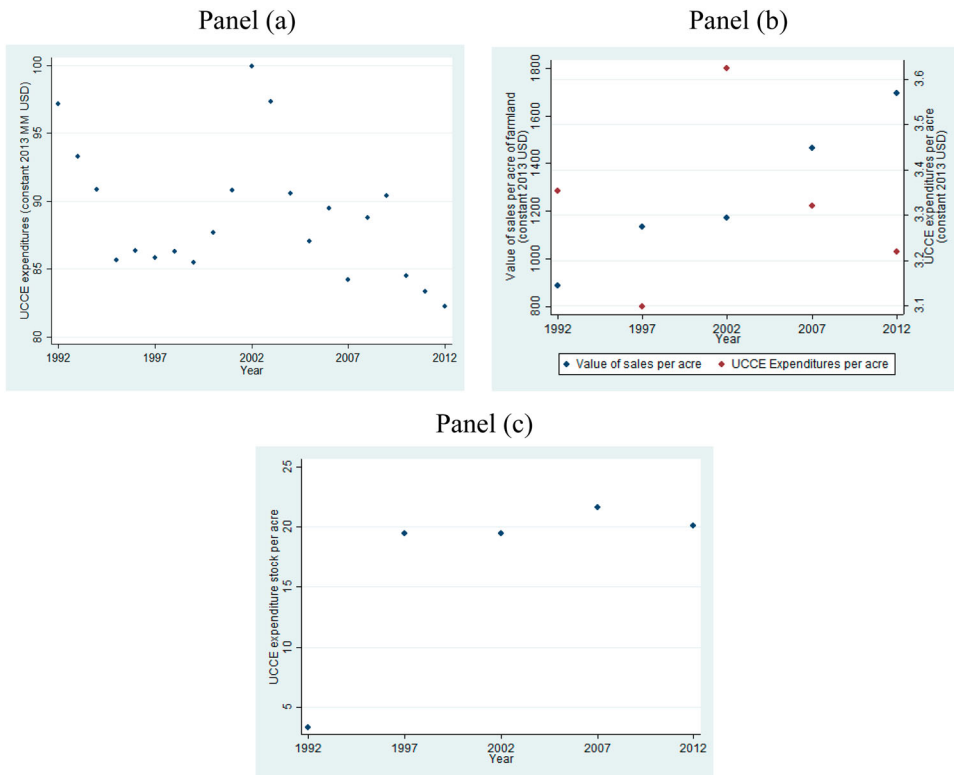


Figure 2. State-level UCCE extension expenditures, and their relationship with total value of sales per acre of farmland. Panel (a) Total expenditures by UCCE for 1992–2012 (constant 2013 million USD). Panel (b) Total value of sales per acre of farmland and contemporaneous UCCE extension expenditures per acre for 1992–2012 (constant 2013 USD). Panel (c) Sum of current and last five years' UCCE extension expenditures per acre of farmland for 1992–2012 (constant 2013 thousand USD).

depreciation rate¹⁷ to be zero. This implies that all old knowledge remains effective, and each of the five expenditure lags in the expenditure stock variable has equal impact. The coefficients for this regression are reported in column (1) of Table 2. Results indicate that the coefficient for stock of UCCE extension expenditure equals 1.05, and is statistically different from zero at a 10 percent level of significance. This implies that a \$1 increase in the expenditure stock (accumulated over the last five years) leads to an extra \$1.05 in the value of sales per acre, on average. Harvested acres measured as a share of total farmland has a negative coefficient with total value of sales per acre, but this effect is not statistically different from zero.¹⁸

The marginal value of hired labor per acre of farmland (measured in total sales per acre) is \$23,262. Hired labor accounts for nearly 33 percent of all farm employment and is responsible for about 60 percent of all farm work in the U.S., according to Martin and Jackson-Smith (2013). The labor force is largely born abroad and has become more important for larger farms in the country. Hired labor employment per acre has undergone a 22 percent decrease between 1992 and 2012 (Bureau of Labor Statistics *n.d.*). In the case of California, hired labor constituted 65 percent of the farm workforce in 2014 (Martin 2018).

The average cost of hired labor is about \$10,385 for our sample (average computed over counties and years), with an average per acre cost of less than \$1. Therefore, for additional hired labor, there is a net gain of nearly \$23,000 in total value of sales per acre.¹⁹ Machinery has a positive coefficient, according to our findings, but the effect is not statistically significant. Acres on which chemicals were applied as a share of total acres of farmland show a statistically significant increase of \$1,248 on county productivity. Our data indicate a 43 percent increase in acreage of chemical application as a share of total farmland over the period 1992–2012, contributing to the increase in productivity seen over the same period. Average cost of chemicals per acre of application is \$152. When calculated in per acre farmland terms, this amount becomes less than \$1.²⁰

Therefore the \$1,248 addition to the total value of sales per acre is also the net impact of an acre of chemical application per acre of farmland. An additional primary-occupation farmer in a county impacts productivity negatively (nearly $-\$1.2$ towards total value of sales/acre) in our analysis. This impact is statistically different from 0 at 1 percent level of significance, which could be interpreted as less-efficient producers in the agricultural sector whose primary occupation is farming.

Previous literature provides empirical evidence of movement of educated and more efficient farmers to off-farm work, both for the U.S. (Huffman 1980) and internationally for Pakistan (Fafchamps and Quisumbing 1999). The more efficient farmers may have obtained multiple jobs or careers, thereby leaving the less efficient ones as primary-occupation farmers, which is captured by our estimated coefficient in Table 2.²¹

Columns (2)–(8) of Table 2 report coefficient estimates for our original model with different values of knowledge depreciation rates (represented by the δ -values in the heading of each column in Table 2). For δ ranging between 5 and 9 percent, represented by columns (2)–(5), the coefficient of the expenditure stock variable changes from \$6.70 to \$7.18 at a 5 percent level of significance. The coefficients of other control variables are very similar for the different depreciation rates. The coefficient of the UCCE extension expenditure stock variable increases from \$7.30 to \$8.60, between 10 and 20 percent knowledge depreciation rate values. We test knowledge depreciation rates beyond 20 percent, which are reported in Appendix Table A1. Results indicate up to 49 percent depreciation of knowledge for our data set, and we observed positive, increasing coefficient estimates for UCCE extension expenditures stock. Beyond 50 percent, the coefficient estimate becomes statistically insignificant. This implies that the contribution of UCCE expenditure stock towards productivity improves under the assumption of a dynamic system in which old knowledge is replaced up to a threshold depreciation rate, while controlling for everything else. Beyond this rate of depreciation, the impact of UCCE extension expenditures stock on agricultural sales per acre becomes insignificant.

Knowledge stock with a 100 percent knowledge depreciation rate is represented by current period UCCE extension expenditures. In such case, all previous expenditures become obsolete in terms of their effect. Regression results are reported in column (9) of Table 2. We see that while coefficients for all other control variables remain similar to the depreciated knowledge cases, the coefficient for the extension expenditure stock variable becomes negative ($-\$31.14$) and significantly different from 0, at a 5 percent level of significance. This implies that current expenditures reduce current total value of sales per acre by nearly \$31. This negative coefficient could capture the allocation of a higher value of resources for counties that have experienced low performance during

Table 2. Regression results for models with total value of agricultural sales per acre of farmland as dependent variable, and UCCE expenditures stock expressed as sum of past expenditures undergoing depreciation in panel dataset.

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Total value of agricultural sales per acre of farmland	$\delta = 0$	$\delta = 0.05$	$\delta = 0.07$	$\delta = 0.08$	$\delta = 0.09$	$\delta = 0.1$	$\delta = 0.15$	$\delta = 0.2$	$\delta = 1$
R&D expenditure stock per acre farmland	1.05*	6.70**	6.94**	7.06**	7.18**	7.30*	7.93*	8.59*	-31.14**
	(0.54)	(3.29)	(3.43)	(3.50)	(3.57)	(3.65)	(4.04)	(4.47)	(13.46)
Acres harvested per acre of farmland	-631.9	-630.6	-632.9	-634.1	-635.3	-636.5	-642.8	-649.3	-580.8
	(2,380)	(2,368)	(2,367)	(2,367)	(2,367)	(2,367)	(2,366)	(2,366)	(2,431)
Hired labor per acre of farmland	23,262***	23,398***	23,408***	23,413***	23,419***	23,424***	23,451***	23,480***	25,089***
	(7,280)	(7,121)	(7,126)	(7,128)	(7,131)	(7,133)	(7,146)	(7,161)	(7,435)
Machinery per acre of farmland	28,253	29,470	29,536	29,570	29,605	29,641	29,830	30,037	46,645
	(33,349)	(32,852)	(32,853)	(32,855)	(32,856)	(32,857)	(32,869)	(32,886)	(35,195)
Chemicals per acre of farmland	1,248*	1,247*	1,247*	1,247*	1,247*	1,247*	1,248*	1,249*	1,407**
	(631.5)	(627.4)	(627.8)	(627.9)	(628.1)	(628.3)	(629.3)	(630.3)	(580.3)
Primary occupation	-1.19***	-1.19***	-1.19***	-1.19***	-1.19***	-1.19***	-1.19***	-1.19***	-1.14***
	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.24)
Average age	-43.78	-42.52	-42.73	-42.83	-42.94	-43.05	-43.61	-44.20	-34.04
	(34.83)	(32.94)	(33.02)	(33.07)	(33.12)	(33.17)	(33.42)	(33.71)	(38.19)
Constant	2,154	2,111	2,122	2,128	2,134	2,140	2,170	2,202	1,837
	(1,986)	(1,880)	(1,884)	(1,887)	(1,889)	(1,892)	(1,906)	(1,921)	(2,131)
Observations	249	249	249	249	249	249	249	249	249
R-squared	0.944	0.945	0.944	0.944	0.944	0.944	0.944	0.944	0.943
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year time trend	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

that fiscal year, or cutbacks for a particular county that has performed well. As Foster and Rosenzweig (1995) found new technology takes a while to be adopted, and its full impact is observed over time. So, a combination of the two may explain the results we obtained. Therefore, consideration of only the current period expenditures on measuring the impact of UCCE research and outreach expenditures on productivity only tells part of the story. A more complete picture requires understanding how the current stock of research-based knowledge impacts productivity. The current knowledge stock is the sum of old and new knowledge produced through expenditures on R&D and outreach, thereby providing a more complete understanding of the long-term impact of UCCE expenditure on county productivity.²²

The trend we observe in the UCCE extension expenditure coefficients as the rate of depreciation grows from 0 to 100 percent (Table 2, Appendix Table A1) presents an increase up to 50 percent depreciation and then a decline. At that range, we observe either insignificant coefficients or negative coefficients (for 100 percent depreciation). One possible interpretation is that the more frequent the replacement of knowledge the higher the impact of funds spent on knowledge creation and dissemination. This is up to a given point (in California, it is 50 percent) at which the effectiveness of the knowledge stock decreases/drops. When knowledge replacement is 100 percent, meaning every year all knowledge becomes obsolete and needs to be replaced, the UCCE system is not efficient, leading to a negative coefficient of its expenditures stock.

5.2. Estimation of individual county-level impact

Empirical results in Table 2 inform how UCCE impacts average county-level productivity. However, we now want to test how the impact of UCCE expenditure on productivity varies across counties. Heterogeneous impact across counties can result from various reasons. In particular, differences in the resource base (e.g. land, water, climate) in the various counties, and the composition of the crops grown, can lead to differences in extension productivity (Lampach, Nguyen Van, and Nguyen 2018). From a policy perspective, this analysis is an important contribution to the literature, because it allows evaluating policies that affect certain localities that face different climatic or soil fertility. To achieve this, we have made some modifications to our original model. The main empirical model remains unchanged, but we include interaction terms between dummy variables representing each county and its UCCE expenditures into the old model. Regression coefficients for 23²³ counties are reported in Table 3 for knowledge depreciation rates ranging from 0 to 20 percent, and it includes only the estimates of the coefficients for the counties that interacted with the UCCE expenditures.²⁴ The first row in Table 3 reports the impact of UCCE in Alameda County on total value of sales, which is negative for all used knowledge depreciation rates, and is statistically insignificant. Alameda is the benchmark county for the coefficient estimates in our empirical analysis. Fresno County records the highest positive coefficient of UCCE expenditures stock. It varies from \$25²⁵ to \$191, depending on total value of sales per acre, for knowledge depreciation rates ranging between 0 and 20 percent, respectively.

The coefficients for Fresno County are the highest (\$24 to \$190) and statistically different from 0 at 1 percent level of significance. San Bernardino County has the next highest impact on total value of sales per acre, which ranges between \$10 and \$82. The

Table 3. Coefficients of differential county-level impacts of UCCE expenditures on total value of sales per acre, at different levels of knowledge depreciation rates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	$\delta = 0$	$\delta = 0.05$	$\delta = 0.07$	$\delta = 0.08$	$\delta = 0.09$	$\delta = 0.1$	$\delta = 0.15$	$\delta = 0.2$
Alameda	-0.89	-4.89	-5.14	-5.28	-5.41	-5.55	-6.29	-7.14
Amador	-4.18**	-25.15**	-26.24**	-26.80**	-27.37**	-27.95**	-31.02**	-34.38**
Calaveras	-3.17**	-18.88**	-19.69**	-20.11**	-20.53**	-20.96**	-23.24**	-25.73**
Fresno	24.72***	143.71***	149.36***	152.23***	155.19***	158.15***	173.81***	190.87***
Humboldt-Del Norte	-6.08***	-34.51***	-36.24***	-37.14***	-38.06***	-39.01***	-44.08***	-49.82***
Imperial	1.89**	10.71*	10.94*	11.05*	11.15*	11.25*	11.75*	12.15
Kern	7.98***	46.46***	48.18***	49.06**	49.95***	50.85***	55.61***	60.71***
Los Angeles	0.18	0.75	0.76	0.76	0.76	0.76	0.76	0.75
Modoc	-6.28***	-33.14**	-34.41**	-35.07**	-35.73**	-36.41**	-39.94**	-43.77**
Monterey	6.05**	33.74**	35.02**	35.68**	36.34**	37.01**	40.52**	44.28**
Napa	3.02***	18.78***	19.53***	19.91***	20.29***	20.69***	22.77***	25.03***
Orange	1.65***	10.68***	11.09***	11.31***	11.51***	11.73***	12.87***	14.10***
San Bernardino	9.84***	61.10***	63.56***	64.83***	66.11***	67.42***	74.36***	81.95***
San Diego	1.16***	6.72***	7.00***	7.14***	7.28***	7.42***	8.21***	9.07***
San Francisco-San Mateo	0.65***	4.20***	4.30***	4.36***	4.41***	4.46***	4.71***	4.94***
San Joaquin	3.20***	22.14***	23.01***	23.46***	23.91***	24.37***	26.79***	29.39***
Santa Clara	0.00	0.42	0.38	0.36	0.34	0.31	0.17	-0.02
Santa Cruz	2.06***	10.55***	11.00***	11.23***	11.46***	11.70***	12.96***	14.36***
Siskiyou	-6.79***	-38.07***	-39.74***	-40.62***	-41.50***	-42.40***	-47.23***	-52.59***
Sonoma	4.23***	24.83***	25.78***	26.27***	26.76***	27.26***	29.87***	32.65***
Stanislaus	2.60**	15.62***	16.07***	16.30***	16.53***	16.76**	17.91**	19.06**
Tulare	9.54***	54.63***	56.71***	57.77***	58.85***	59.95***	65.73***	71.97***
Ventura	1.94*	11.12**	11.52**	11.72**	11.93**	12.13**	13.23**	14.40**

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

third highest statistically significant impact is obtained for Tulare County, which ranges between \$10 and \$72.

The coefficient estimates for Los Angeles and Santa Clara counties indicate no significant impact of UCCE expenditures stock. Kern, Monterey, San Joaquin, Stanislaus, and Ventura counties, which are among the top 10 agricultural counties, have positive and statistically significant impacts reported in columns (1)–(8) of [Table 3](#). Amador, Calaveras, Humboldt-Del Norte, Modoc, and Siskiyou counties have negative statistically significant coefficient estimates for knowledge depreciation rates ranging from 0 to 20 percent.²⁶ For Imperial County, we observe that for 20 percent knowledge depreciation rate, the value of the coefficient estimate does not remain statistically different from 0. This result implies that adoption of new technologies at these rates may incur high costs and can stop impacting productivity positively. Los Angeles, San Francisco-San Mateo, and Santa Cruz counties do not report high impact on productivity, even though they are among the counties recording some of the highest expenditures made by UCCE.²⁷

Overall, Fresno, Kern, Monterey, Tulare, and San Bernardino counties record the largest impacts of UCCE expenditure stock. The first four counties are among the top 10 agricultural producers in the state. All these counties are also among the biggest producers of some of the most high-profile agricultural products in terms of receipts, e.g. grapes, almonds, strawberries, and citrus among fruits and nuts, tomatoes and lettuce among vegetables, and dairy, livestock, and poultry. The results discussed above provide better understanding of UCCE's impact on individual county-level productivity. More productive counties in general report higher impact of UCCE presence.²⁸

5.3. Substitution between inputs of agricultural production

A pertinent issue with respect to this paper is the substitutability between UCCE expenditure stock and other inputs of production. This is particularly relevant because some counties may face scarcity of one or more of the traditional inputs, and it would be an important contribution if expenditures on UCCE can be a substitute for the said input. For this analysis, we use the inputs that have been found to have a statistically significant positive impact on productivity, such as hired labor, and acres of chemical application. Since number of primary occupation farmers brings down productivity, it is a 'bad' input. We have used a linear model in this paper, which makes the calculations simpler, under the assumption of constant marginal productivity. We use the equation of marginal rate of technical substitution (MRTS):

$$MRTS_{1,2} = -\frac{MP_1}{MP_2} \quad (6)$$

Using our regression coefficients in [Table 2](#) (for $\delta = 0.07$ as an example), we obtain the value of this ratio for hired labor, which equals -0.0002965 ($-6.94/23,408$). This means that a \$1 increase in UCCE extension expenditure stock per acre of farmland will lead to a reduction in hired labor per acre by nearly 0.0003 workers, keeping total value of sales per acre constant. This is a reduction of nearly 1.5 percent, compared to the mean value of this variable ([Table 1](#)). For the next significant input, which is acres of chemicals applied as a share of total farmland acres, we find that MRTS equals -0.00556 ($-6.94/1,247$). This means that a \$1 increase in UCCE expenditure stock per acre of farmland

will lead to reduction in the share of chemicals applied per acre by nearly 0.006, keeping total value of sales per acre constant. This again is a reduction of about 1 percent, compared to the mean value of this variable (Table 1). Similar trends in substitution were reported in Goodhue, Klonsky, and Mohapatra (2010), suggesting (in their work) that almond grower education programs can have a significant effect on pesticide use decisions. We observe that substitution effect is low between the aforementioned traditional inputs and UCCE expenditures, thereby hinting at complementarity between each of them and UCCE expenditures. These estimates are a starting point in the discussion on the topic, which has very important policy implications not only for California but also for the entire nation.

Using the coefficient estimates, we calculate the rise in total value of sales per acre for our sample, using mean UCCE extension expenditures per acre. That amounts to \$41 ($\6.2×6.6, where \$6.2 is mean UCCE extension expenditures, and 6.6 is the mean value of the coefficient for UCCE extension expenditure stock²⁹). Multiplying this \$ value by mean farmland acres in our dataset over the analyzed period provides a total increase in value of sales amounting to \$22,165,359 ($\$41 \times 540,618.5$), on average, per county. The average per county real UCCE extension expenditure for the 20-year period between 1992 and 2012 amounts to \$1,778,146, which implies an average per county profit of nearly \$20 million ($=22,165,359 - 1,778,146$), due to the UCCE extension expenditures on research and development, and outreach. This provides some evidence of the scale of impact UCCE expenditures stock has on average county productivity. The same calculations for individual counties can provide a more in-depth understanding of the effects on them for policy planning.

5.4. Discussion and possible caveats

We observe (Table 1) allocated extension expenditures per acre with a mean of 6.21 and a standard deviation (SD) of 8.59, suggesting a wide difference across the counties. Decisions on allocation of extension funding at the county level depend on many criteria, including the county's productivity and long-term planning criteria (development objectives), and even political considerations and lobbying, as was already suggested in our paper.

While we are running contemporaneous regressions (i.e. the dependent variable, sales, and all regressors dated at time t), the decision making does not take place contemporaneously. That is, the yearly spending budgets are set prior to whatever economic activity goes on in the county during that year. The budget process happens before the total sales for that year are known. It seems natural to think that the effect runs from spending budget to sales, rather than the other way around. Nevertheless, we have only five years of production and sales data, and it may be reasonable to think that productive counties in a year can be favored with larger budgets the following years. But this is not the case. Scrutiny of Figure 1 suggests, for example, that Fresno, which is one of the most productive counties, had UCCE expenditure of about \$3 per acre in 1992 and in 2007. On the other extreme, Alameda, which is one of the least productive counties, had UCCE expenditure of about \$7 per acre in 1992 and in 2007. Thus, over time we do not observe overall big changes in UCCE expenditure that are triggered by the productivity of the county, and the case for endogeneity becomes weaker, if not irrelevant. The large SD of the extension

expenditures reinforces the aim of our analysis that explains the variation in sales as a function of the variability of UCCE expenditures.

A caveat of this paper is that spillover effects across counties have not been included in the model. The empirical model assumes that there is no spillover, but this effect can be incorporated in future work. This paper estimates a simplified model of agricultural sales as a function of inputs, including UCCE expenditures stock, to provide a county-level impact of UCCE expenditures on R&D and outreach on productivity, which can provide policymakers with a reference point for policy decisions in California. Another caveat is the relatively short period of time (21 years), considered in our analysis. Longer time-series data would lead to higher values of benefits from the estimated impact equations.

6. Summary, conclusion, and policy implications

6.1. Summary and conclusion

We estimate the impact of the University of California Cooperative Extension (UCCE) on county-level agricultural productivity in California, using a model representing a relationship between value of agricultural sales as a proxy for productivity, and quantitative inputs of production, including UCCE expenditures. Our analysis is aggregated to the county level because UCCE operates from county offices across the state. We obtained data for UCCE budgets for all agricultural research and development (R&D), and outreach/dissemination projects for 50 county offices statewide for the years 1992–2012 (covering 57 counties). Stock of knowledge produced through UCCE extension expenditures on R&D and outreach is modeled as a function of a stream of current and depreciated past expenditures, and used as our independent variable. Data on factors of agricultural production, such as harvested acreage, hired labor, chemical applications, machinery, average farmer age, and number of primary occupation farmers were obtained from the Census of Agriculture conducted by United States Department of Agriculture (USDA) for five census years, spanning over 1992–2012. Productivity is represented by total value of sales per acre of farmland, using data from the Census of Agriculture.

To estimate the impact of UCCE expenditures on agricultural R&D and outreach/dissemination on productivity, we construct a stock of expenditures. We use current and five lagged values of UCCE expenditures, and a range of different depreciation rates from the literature. The intuition is that old knowledge depreciates over time, therefore older expenditures enter the model at a depreciated value. We analyze our model using depreciation rates ranging from 0 to 9 percent, and then 10, 15, and 20 percent following Griliches (1980, 1986). Regression results indicate that UCCE's stock of expenditures has a statistically significant impact on total value of sales per acre, which varies from nearly \$1 to \$9, for depreciation rates between 0 and 20 percent. For higher rates of depreciation of expenditure, the coefficient becomes statistically insignificant. Results therefore suggest that for more dynamic systems with frequent innovations, UCCE's efforts have a higher impact on productivity. This effect, however, becomes insignificant with very high (50 percent and above) levels of depreciation. For a knowledge depreciation rate of 100 percent, we find that the coefficient becomes negative (-\$31), and this effect is statistically different from 0. This result likely captures the allocation of higher expenditures on counties that have

reported lower performance during the year, or cutbacks for a particular county that is performing well. Therefore, our results agree with the existing literature, which suggests that old expenditures impact current productivity positively, and their exclusion tells us only a partial story. The coefficients we have obtained in this study indicate that there is room for improvement in extension research and outreach, and that introduction of new research-based knowledge and technology improves productivity. Results also suggest that primary-occupation farmers may be less efficient than those who are able to maintain more than one profession. Efforts could be focused towards improving any existing gaps in efficiency among farmers in different counties.

6.2. Policy implications

The results of our analysis can guide policymakers during a period of political pressure to reduce public spending for agricultural extension in the state. The county fixed effects results allow a more targeted policy intervention on higher and lower performing regions (e.g. counties). Empirical results include the impact of UCCE's expenditure stock on individual counties. By controlling for individual county and fixed-year effects that may be driving productivity in that county, we find that some of the major agricultural counties in California record high positive impacts of UCCE expenditures stock. Out of the 50 county offices in our study, we observe that UCCE expenditures stock has a significant impact on 21 counties for all values of knowledge depreciation. We observe a statistically significant negative impact on a few counties, such as Amador, Calaveras, Humboldt-Del Norte, Modoc, and Siskiyou. For two counties, the impact is not statistically different from 0. In terms of policy, these coefficients can be used as reference points for allocating budgets to different counties.

Extension efforts could be targeted to the counties with inconclusive (statistically insignificant) or negative impacts. Monetary impact of cutbacks on county productivity could also be calculated, using the estimates of extension expenditures in this paper. The analysis driven by county performance helps design policies with heterogeneous focus, which has been more relevant when public funds have to be allocated among heterogeneous performing recipients of these funds.

And finally, as shown in Section 5.3 extension introduces substitutability of traditional inputs with extension knowledge so that higher expenditure on extension in some of the lower-performing counties can substitute for other traditional inputs, which may be scarce in supply. In particular, our analysis highlighted and measured substitution of extension knowledge for labor and chemicals.

Notes

1. <http://www.csrees.usda.gov/qlinks/extension.html>
2. http://extension100years.net/en/administration/about_us/chancellors_office/extension/about-smith-lever/
3. We use value of agricultural sales to measure agricultural productivity in this paper. Although these two terms are not the same because we do not account for cost of production. Value of agricultural sales is used in this analysis as a proxy of the county's agricultural sector productivity, following a similar methodology by OECD (2001).

4. We use the concept of knowledge production function (KPF). The development of KPF is not the focus of this paper. We provide general information about our estimates, but the reader is referred for more details to Chatterjee, Dinar, and González-Rivera (2018).
5. <http://www.csrees.usda.gov/qlinks/extension.html#today>
6. http://ucop.edu/communications/_files/mini-brochures/ANR_minibrochure.pdf
7. We are unable to account for undocumented labor in this analysis because the data on undocumented labor is not available in the USDA agricultural census. This data source does not provide information on family labor. However, Martin (2018) suggests that the share of hired labor of the total labor employed in California is 65 percent during the year of the analysis in this paper. While we capture the majority of the labor employed on farms in California, it is likely that our results provide an overestimation of the impact of labor on value of agricultural sales per acre.
8. While production decisions are made at the farm level, this approach captures the results of such decisions and decisions of extension expenditure allocation on a per acre of farmland to control for size effects.
9. We use a simple linear relationship in this paper; other cases with non-linear relationships between the inputs and the dependent variable could be potentially used for the analysis. We estimated different models and decided to report the linear model coefficients. We do not consider the extreme cases in which there is only one input, UCCE expenditures, or labor, in this analysis.
10. The choice of the number of lags is also guided by unavailability of data beyond five lags.
11. For clarification, certain type of machinery could be more important than other types of machinery, and the impact of older machinery may have depreciated. The AG Census does ask respondents to indicate how old the machines are, and then specifically asks how many were used in the cultivation process that year. However, there is no way to know from the responses the exact type of machinery (and age) used by the farm. For that reason, we did not use the detailed information but instead used a count variable for machinery.
12. In the context of measuring production input at the county level, Huffman (1976) uses different approaches for some of the inputs in the production process with data for 1960. For example, Huffman (1976) uses family labor+hired labor, while we use only hired labor. Our data source (FRIS) provides only hired labor data for 2014, mainly because in 2014 the structure of the agricultural farms in California transformed, compared with 1960, and consist of much more hired labor (Martin 2018). While Huffman (1976) had access to fertilizer input data in the form of price-weighted primary plant nutrients, that work doesn't include data on chemicals such as pesticides.
13. This is the mean value for UCCE expenditures per acre for each of the five census years.
14. The mean value of the share of acres of harvested land to total farmland acres calculated, based on our entire data set, equals 0.25. The calculated percentage of total acres harvested, to total acres of farmland (across all counties, and all years) amounts to 30 percent. This figure is very similar to that reported in the 2002 report by the University of California, Davis: http://aic.ucdavis.edu/publications/moca/moca_current/moca09/moca09chapter1.pdf. It is the result of increased water scarcity during the years for which we use FRIS data, leading to reduction in irrigated acres.
15. The variable that represents 'chemicals and fertilizers' is measured as the ratio of total area on which fertilizers, pesticides, and other chemicals were applied, to total area of farm land. In the Census of Agriculture, farmers are asked to provide a count of the number of acres on which four main types of chemicals are applied to treat diseases and two types of fertilizers are added, including manure. We create a count variable that is divided by total farmland acreage, and the resulting variable can theoretically range, for each farm surveyed, between 0 and n ($n > 1$). The reason is that the same acreage could be reported several times as receiving chemicals and fertilizers.
16. Census of Agriculture highlights, 2012. https://www.agcensus.usda.gov/Publications/2012/Preliminary_Report/Highlights.pdf

17. This is obtained by setting $\delta = 0$ in Equations (4) and (5).
18. We estimated the same empirical model, including individual UCCE expenditure lags as separate independent variables. The estimates indicate that each individual expenditure lag does not have a statistically significant impact. The idea is similar to what the literature suggests. The underlying principle is that the expenditures stock, which generates a knowledge stock, affects productivity, or value of agricultural sales.
19. Expenditure on hired labor is obtained from the agricultural census reports published by USDA. It is divided by total number of hired labor recorded in the census, and then expressed in per acre terms through division by total farmland in acres, all values aggregated at the county level.
20. Expenditure on all chemical and fertilizer application is obtained from the agricultural census reports. It is divided by total number of acres on which application took place, and then expressed in per acre farmland terms through division by total farmland (acres); all values are aggregated at the county level.
21. The above model was estimated, including number of primary occupation farmers per farm for a county as the independent variable instead of number of primary occupations per county. This is to capture the cases in which a primary occupation farmer is cultivating more land and producing less output, or vice versa. The coefficient estimate of the new independent variable is still negative but statistically insignificant.
22. We have estimated a model, including county average temperature and precipitation into the regression model represented by Equation (3), and found that weather variables do not have any significant impact. We also estimated the model with interaction terms between UCCE expenditures stock and our county average temperature and precipitation, and obtained insignificant coefficients.
23. Twenty-seven counties with statistically insignificant coefficients were removed from the analysis to minimize the loss of degrees of freedom.
24. This is done due to space constraint.
25. Numbers are rounded.
26. These counties are all low-ranking counties, in terms of production value. Some of the counties had experienced reduction in agricultural land (<https://www.cdfa.ca.gov/statistics/pdfs/2013/finaldraft2012-2013.pdf>). These counties are located in mountainous regions and specialize in agricultural crops facing harsh market conditions (e.g. pasture) and have difficulties transforming UCCE knowledge into sales.
27. The coefficient estimate for UCCE is statistically insignificant in case of Los Angeles, and small but positive and statistically significant for San Francisco-San Mateo. Through discussions with UCCE officials, we learned that both of these counties include considerable non-agricultural research and outreach work done by UCCE that is not included in our analysis. This may explain why agricultural expenditures on research and outreach may not have any notable impact on agricultural sales in these two counties.
28. We were advised by an anonymous reviewer to try more consistent econometric models. We used procedures in Rabe-Hesketh and Skrondal (2012) to estimate the random coefficient model and a model with consistent estimation of effects of endogeneous time-varying covariates (STATA commands *xtmixed* and *xhtaylor*). The results of these estimations yielded identical coefficients and significance levels to those obtained in our reported results. Therefore, we decided not to present the additional (identical) results. They can be provided upon request by the corresponding author.
29. This is calculated for knowledge depreciation rates ranging from 0 to 20 percent.
30. Few outliers were removed from the diagrams (only) to improve visibility of the names of counties.

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Notes on contributors

Diti Chatterjee is an Economist with A2F Consulting in Bethesda, MD, USA. She works on aspects of economic investment and growth and environmental consequences in developing countries.

Ariel Dinar is a Distinguished Professor of Environmental Economics and Policy at the School of Public Policy, University of California, Riverside, USA. His research addresses agricultural economics and natural and environmental resource economics as well as economic aspects of agricultural extension.

Gloria González-Rivera is Professor of Economics at the University of California Riverside. She is the President and elected director to the board of the International Institute of Forecasters. Her research focuses on the development of econometric and forecasting methodology with applications in financial markets, volatility forecasting, risk management, and agricultural markets.

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Appendix. Additional regression results

Table A1. Ordinary least squares (OLS) regression results show that coefficient estimate for UCCE expenditures stock becomes statistically insignificant beyond 50 percent knowledge depreciation rate (δ).

Dependent Var.	Total value of agricultural sales per acre of farmland						
	$\delta = 0.3$	$\delta = 0.4$	$\delta = 0.45$	$\delta = 0.47$	$\delta = 0.48$	$\delta = 0.49$	$\delta = 0.5$
R&D expenditure stock per acre of farmland	9.95* (5.45)	11.28* (6.60)	10.62* (6.00)	10.89* (6.23)	11.02* (6.35)	11.15* (6.47)	12.45 (7.91)
Acres harvested per acre of farmland	-663.0 (2,366)	-677.2 (2,367)	-670.1 (2,367)	-672.9 (2,367)	-674.3 (2,367)	-675.7 (2,367)	-691.2 (2,370)
Hired labor per acre of farmland	23,540*** (7,193)	23,604*** (7,231)	23,572*** (7,211)	23,585*** (7,219)	23,591*** (7,223)	23,598*** (7,227)	23,671*** (7,272)
Machinery per acre of farmland	30,510 (32,945)	31,055 (33,043)	30,774 (32,988)	30,884 (33,009)	30,941 (33,020)	30,997 (33,031)	31,660 (33,186)
Chemicals per acre of farmland	1,252* (632.5)	1,255* (634.9)	1,253* (633.7)	1,254* (634.2)	1,254* (634.4)	1,255* (634.7)	1,260* (637.4)
Primary occupation	-1.19*** (0.26)	-1.18*** (0.26)	-1.18*** (0.26)	-1.18*** (0.26)	-1.18*** (0.26)	-1.18*** (0.26)	-1.18*** (0.26)
Average age	-45.43 (34.36)	-46.69 (35.11)	-46.06 (34.73)	-46.31 (34.88)	-46.44 (34.96)	-46.56 (35.03)	-47.88 (35.93)
Constant	2,269 (1,956)	2,337 (1,996)	2,303 (1,975)	2,317 (1,984)	2,324 (1,988)	2,331 (1,992)	2,403 (2,040)
Observations	249	249	249	249	249	249	249
R-squared	0.944	0.944	0.944	0.944	0.944	0.944	0.943
County FE	YES	YES	YES	YES	YES	YES	YES
Year Time Trend	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.