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Abstract

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Keywords: Agricultural productivity, University of California Cooperative Extension, public R&D expenditure, R&D lags, California counties.

JEL codes: Q10, Q16, C01, C23.

1. Introduction

The history of American agricultural extension dates back more than a hundred years. The Morrill Act of 1862 established land-grant universities across the country with the purpose of educating the citizens about agriculture, home economics, mechanical arts and other practical professions[1]. According to this 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 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). According to the 1914 Act the extension work involved (a) Developing practical applications of research knowledge, and (b) Giving instructions and practical demonstrations of existing or improved practices or technologies in agriculture. Funding for the Cooperative Extension would come from the Congress to the United States Department of Agriculture, which would then distribute it amongst 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%, with county contribution amounting to 20% of the total (Rogers, 1988).

Through the course of almost a century, the UC 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.

[1] http://www.csrees.usda.gov/qlinks/extension.html

[2] http://extension100years.net/en/administration/about_us/chancellors_office/extension/about-smith-lever/

Today the Extension works in six major areas[3]: *Agriculture, 4-H Youth Development, Natural Resources, Leadership Development, Family and Consumer Sciences,* and *Community and Economic Development.* In this paper however, we focus only on the role of UCCE in agriculture.

California ranks first among the top five producers of agricultural products, according to the California Statistical Review, 2014-15, with crop cash receipts amounting to $53.5 billion. It has been consistently among the top 5 agricultural producers in the U.S. 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, plums, etc. California's cash receipts from agriculture amount to about 13 percent of the nation's total. According to a report[4] by UC Division of Agricultural and Natural Resources (UCDANR), UCCE has a considerable contribution to California's agriculture. UC researchers discovered ways to remove salt from the soils, which helped turn the arid soils in the Central Valley into one of the world's most productive regions. UC-led advancements helped farmers irrigate, plant and prune to raise almond yields, and broccoli production. As many as 40 different varieties of citruses have been bred by UC researchers. About 65 percent of the strawberries produced in the state (which constitute 40 percent of the national production) are from UC-developed varieties. UCCE has helped create a $119 million artisan cheese making industry in Marin and Sonoma counties. California growers have been able to save $65 million and reduce irrigation water usage by 100,000 acre-feet due to the irrigation scheduling services provided by the California Irrigation Management Information System (CIMIS). The Master Gardener program and the Integrated Pest Management System (IPM) have also been highly successful in reducing urban landscape runoff and pesticide use in the state. UCCE has been working in California for the past hundred years, which has contributed significantly to enhancing productivity, making the state a leader in agricultural production and income generation.

With such contributions of UCCE to California agriculture, an economic analysis that can assess the productivity of the UCCE spending would be most important especially during a period of

[3] http://www.csrees.usda.gov/qlinks/extension.html#today
[4] http://ucop.edu/communications/_files/mini-brochures/ANR_minibrochure.pdf

pressure to reduce public spending on agricultural extension. Next we review several relevant studies and distinguish our work from previous published studies.

Alston *et al.* (2009) report that sustained growth observed in the U.S. as well as 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 fifty years. U.S agriculture in general has been experiencing a decline in productivity, according to Ball *et al* (2013). Alston *et al*. (2013) report that public funding allocated towards agricultural R&D has been declining over that period in the country and is the primary reason for decline in productivity growth. Therefore, there is the 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 such as Griliches (1964) estimated a Cobb-Douglas agricultural production function, introducing a research and extension variable along with the conventional input variables. Huffman and Evenson (1993) and Alston *et al*. (1998) analyzed in details factors which 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, and found positive impact of public agricultural research on productivity. Alston *et al*. (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) provide evidence that expenditures on agricultural research provide new knowledge and technologies, which enable improvements in agricultural productivity in US agriculture. Alston *et al.* (2011) reported an own-state payoff of $33.3 and a national payoff of $43.4 (including California and inter-state spillover payoff) for every dollar spent by in California’s research and extension system, for the period 1949-2002.

Most recent studies have aggregated extension and publicly funded R&D into one combined variable in their studies. Jin and Huffman (2016) is one of the few papers that have 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 extension and 67 percent for publicly funded agricultural research.

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 a thousand researchers scattered across the various county offices and the UC Campuses of Berkeley, Davis, and Riverside who are involved in research. The knowledge produced in both basic and applied research is then disseminated to farmers and ranchers by UCCE agents and volunteers. While state level agricultural research could be oriented more towards the general goal of enhancement of productivity, research and extension work carried out at a more local level such as a county could be focused more towards solving local impediments, which then fuel improvements in local productivity.

The main contribution of this paper lies in the estimation of the agricultural production function with extension component for all counties in California, including solely the expenditures allocated by UCCE towards R&D and extension. It captures the impact of an expenditure stock, under the assumption that old expenditures also impact current productivity. The intensity of impact of past expenditures on current productivity however decreases over time. This idea is analogous to the idea of depreciation of old knowledge, and henceforth waning of its impact on productivity. To capture this effect, expenditure stock is created using current and past expenditures data, and different deprecation rates are considered, in order to analyze the impact of UCCE on county level productivity in California for the period 1992-2012.

The remainder of the paper is organized as follows: section 2 outlines the econometric methodology, followed by section 3 that describes the data and variable creation. Section 4 analyzes the empirical results. We end the paper with conclusion and policy implications in section 5.

2. Analytical Framework and Empirical Specifications

Empirical estimation of the impact of public R&D on agricultural productivity uses a production function model, with agricultural productivity as the output, and various market and non-market factors along with expenditures on R&D and extension as the inputs. Griliches (1964), Evenson (1978), Alston *et al*. (1998, 2011), Jin and Huffman (2016), estimated the agricultural production function model. All except Griliches (1964) estimate 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, chemicals etc., 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, farmer education. This paper estimates a linear production function controlling for the major factors of agricultural production.

The above mentioned studies assume that R&D expenditures impact productivity, and the impact is dynamic. This implies that in any given period in time, productivity is impacted by a cumulative stock of past and present expenditures, which is also sometimes referred to as the "knowledge stock" (Alson *et al.;* 1998). The theory is derived from the idea that current research-based knowledge is an accumulation of past and present knowledge; some of the old knowledge depreciates and becomes less effective.

Agricultural output is a function of traditional inputs and agricultural knowledge stock produced through a stream of expenditures on R&D and outreach.

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

where *i* = county, *t* = year, *K* represents stock of knowledge, *FP* represents traditional factors of production, *C* represent other farmer characteristic related control variables, *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:

$$K_{it} = f\left(E_{it}, E_{i,t-1}, E_{i,t-2}, E_{i,t-3} .. E_{i,t-L}\right) \qquad (2)$$

where *E* denotes expenditures by UCCE, and *L* denotes total number of time lags. For more on the knowledge production function that we estimated, see Chatterjee et al. (2016).

The corresponding econometric production function we estimate is:

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

where i = 1, 2, ...50; t =1992, 1997, 2002, 2007, 2012.

y is the total value of sales of agricultural products per acre of farmland,

K is the stock of knowledge,

L is acres harvested,

HL is hired labor,

M is machinery,

C is acres on which chemicals are applied,

PO is number of primary occupation farmers,

A is average age of farmer,

φ is the county fixed effects variable,

F is the year fixed effects variable,

and ε is the error term.

All the above variables are expressed in terms of per acre farmland.

The above model is based on the assumption that UCCE expenditures on R&D and outreach are allocated towards research that minimizes the impact of county level temperature and precipitation variability on productivity. In the next model, we include county level annual mean temperature and precipitation to test if our assumption is correct. The empirical model we estimate is:

$$y_{it} = \alpha + \beta_1 K_{it} + \beta_2 L_{it} + \beta_3 HL_{it} + \beta_4 M_{it} + \beta_5 C_{it} + \beta_6 PO_{it} + \beta_7 A_{it} + \beta_8 T_{it} + \beta_9 P_{it} + \beta_{10} T_{it}^2 + \beta_{11} P_{it}^2 + \rho\varphi_i + \theta F_t + \varepsilon_{it} \quad (4)$$

The above model has all the variables from model (3), with additional weather variables such as weighted mean of county level temperature and precipitation represented by T_{it} and P_{it} respectively, and the square terms for each. These are introduced with the aim of capturing the non-linear relationship between the input variables and total value of sales per acre.

The variable for knowledge stock enters our production function equation as a sum of current expenditure and a depreciated sum of last period's knowledge stock:

$$K_{it} = E_{it} + (1 - \delta)K_{it-1} \qquad (5)$$

In (5), δ is the rate of depreciation of the stock of existing knowledge. Alston *et al.* (1998) and Griliches (1998) observed that some knowledge produced through research and development process depreciate through time and become obsolete. The rate of depreciation has varied for different studies. Griliches (1980; 1986) implements knowledge depreciation rates of 0, 10, 15, and 20 percent. Adams (1990) estimates an annual depreciation rate of 9 to 13 percent. Khan and Salim (2015) sets a depreciation rate of R&D at 8 percent in their study. For the purpose of this study we estimated models (3) and (4) for depreciation rates ranging from 0 to 20 percent and higher and compare our results.

Pardey and Craig (1989) concludes that at least 30 years of lagged variables may be optimal and may capture all the impact of research on agricultural output. Alston *et al.*(2008; 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 4 year lags for public agricultural extension in their empirical analysis. For our study we include 5 lagged values of UCCE expenditures in our construction of knowledge stock, which is calculated using the following equation[5]:

$$K_{it} = E_{it} + (1 - \delta)E_{it-1} + (1 - \delta)^2E_{it-2} + (1 - \delta)^3E_{it-3} + (1 - \delta)^4E_{it-4} + (1 - \delta)^5K_{it-5} \qquad (6)$$

A pertinent issue in terms of empirical analysis is that of model selection. One may suggest the existence of endogeneity in the allocation of UCCE budgets. However, through interviews of UCCE officials we rejected that hypothesis. The interviews revealed that county level UCCE budgets are allocated depending on the overall state and federal budgets 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 exogenous, and to a large extent independent of the level of productivity of the county's agricultural sector.

We empirically test our model with different depreciation rates to examine if it affects the coefficient of knowledge stock on productivity; and if it does, then to what extent. Regression results are reported in section 4.

[5] The choice of the number of lags is also guided by unavailability of data beyond 5 lags.

3. Data

For this paper we use agricultural census data for the years 1992, 1997, 2002, 2007 and 2012, for the information on value of agricultural sales, factors of production, and farmer characteristics. The agricultural census survey is conducted by US Department of Agriculture (USDA) at the national level every 5 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 annual budget data by county offices for the years 1992 through 2012, which was available for 50 county offices. Some counties in our dataset 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, hence it is excluded from the analysis. Henceforth, we will refer to UCCE budget data as expenditures on R&D to avoid ambiguity.

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. The variable 'Chemicals' is the ratio of the sum of all acreage on which fertilizers and pesticides were applied, to total farmland. 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 primary occupation as the second farmer characteristic variable.

Data on average monthly precipitation and temperature for our study is collected from National Oceanic Atmospheric Administration (NOAA), for all active weather stations in California. This data is used to create annual averages for each weather station. Then these stations are matched to the counties in our sample following Burgess et al. (2011). County level weighted annual average temperature and precipitation variables are generated using a weighted average formula: the weights are the inverse of the distance between a station and centroid of a county, for all stations within 50 miles of the centroid.

Summary statistics for the entire data set (N=250, 50 counties x 5 years) are reported in Table 1. Mean total value of sales per acre for our sample is $1316, and UCCE expenditures per acre is nearly $6[6]. One-fourth of an acre of farmland is harvested on average[7]. 1 unit of hired labor is employed per 50 acres of farmland, and 1 unit of machinery per 100 acre. Chemicals and fertilizers are applied to nearly two thirds of an acre of farmland[8]. Average farmer age in the state is 57.2 years, comparable to the national figure of 58.3 years.[9] Average value of temperature and precipitation, calculated for the entire data set amount to about 60 degrees *F*, and 2 inches respectively.

Figure 1 shows the relation between total value of sales per acre and UCCE expenditures per acre for each year, for all counties. We can observe a positive correlation (Appendix Table A2) between expenditures and productivity (sales). We also observe very high expenditures for counties like Los Angeles and San Francisco-San Mateo. Los Angeles county agricultural products includes alfalfa, one of the most important crops in that region. Its average total value of sales per acre is $2547, which is close to double the sample mean of $1316. Mean UCCE expenditures per acre for the county equals $30, which is nearly 5 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 UCCE expenditures per acre of $45, and mean total value of sales per acre of $3283.

[6] This is the mean value for UCCE expenditures pre acre for each census year.

[7] 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%. This figure is very similar to that reported in the 2002 report by UC Davis: http://aic.ucdavis.edu/publications/moca/moca_current/moca09/moca09chapter1.pdf

[8] The variable which 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 Agricultural Census, farmers are asked to provide a count of the number of acres on which 4 main types of chemicals are applied to treat diseases, and 2 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 acre could be reported several times as receiving chemicals and fertilizers.

[9] Census of Agriculture highlights, 2012. https://www.agcensus.usda.gov/Publications/2012/Preliminary_Report/Highlights.pdf

Santa Cruz has the highest average value of sales per acre among all counties, which equals to $6902; its mean UCCE expenditure per acre of $24. The highest amount of cash receipts for the county comes from strawberries, raspberries and other berries, followed by nursery crops and vegetables like brussel 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 of the paper discusses the issue of substitutability of traditional inputs with UCCE expenditures, for policy purposes.

State level expenditures (in constant 2013 USD) by UCCE show an overall downward trend in Figure 2, Panel (a). Expenditures started falling after 1992, before they started to go up again in 1999, increasing to the maximum point in 2002. Since 2009 we observe a steady decline in expenditures, probably due to the financial crises faced by the State of California and the University of California System. 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, total value of agricultural sales per acre of farmland has risen (from $889 to $1693), by 90 percent. Real expenditures made by UCCE normalized per acre have remained relatively unchanged over these census years, ranging between $3-$4. Over the same period of time we observe a 12 percent reduction in acres of farmland in the state, from 29 million acres in 1992 to 25.5 million in 2012. If we consider the stock of expenditures instead of expenditures for the current year only, then the picture is different. In Figure 2, Panel (c) we observe that the expenditures stock (sum of current and 5 previous year's expenditures) per acre has undergone a steady growth over the same period. Therefore, even though the expenditures made by UCCE has fallen over time, the expenditure stock per acre of farmland has risen over this period. We observe a decline in the 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 a positive relationship between this cumulative input and productivity (measured as sales per acre) over the period of our study.

4. Results

4.1 Mean county level impact of UCCE

Empirical results of our paper are reported in Table 2. We have considered a number of cases; in the first case, we consider knowledge depreciation rate[10] to be zero. This implies that all old knowledge remains effective, and each of the five expenditure lags in the expenditure stock variable have equal impact. The coefficients for this regression are reported in column (1) of Table 2. Results indicate that the coefficient for stock of expenditure equals 5.25, and is statistically significant from zero at 10 percent level of significance. This implies that a dollar increase in the expenditure stock (accumulated over the last 5 years) leads to an extra $5.25 in the value of sales per acre, on average. Harvested acres (a measure of economies of scale) as a share of total farmland has a negative coefficient with total value of sales per acre, but this effect is not statistically significant from zero.

The marginal value of hired labor per acre of farmland (measured in total sales per acre) is about $23,000. 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 bigger farms in the country. Hired labor employment per acre has undergone a 22 percent decrease between 1992 and 2012. The average cost of a hired labor is about $10,385 for our sample, (average computed over counties and years) with an average per acre cost of less than a dollar. Therefore for an additional hired labor, there is a net gain of $23,000 to total value of sales per acre.[11] 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 reports a statistically significant increase of $1,248 on county productivity. Our data indicates a 43 percent increase in acreage of chemical application as a share of total farmland over the time of 1992-2012, contributing to the increase in productivity seen over the same period. Average cost of chemicals per acre of application is $152; this quantity when calculated in per acre farmland terms becomes

[10] This means we plug in $\delta=0$ in equation 4 and 5.

[11] 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 farm land in acres, all values aggregated at the county level.

less than $1[12]. Therefore the $1,248 addition to 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 (-$1.2 towards total value of sales/acre) in our analysis; this impact is statistically different from zero at one percent level of significance. This could be interpreted as existence of less efficient farmers in the agricultural sector whose primary occupation is farming.

Studies provide empirical evidence of movement of educated and more efficient farmers to off-farm work, both for the U.S (Huffman, 1980) and internationally (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.

Columns (2)-(8) of Table 2 report coefficient estimates for our original model for different values of knowledge depreciation rate (represented by the δ-values on top of each column in Table 2). For δ ranging between 5 to 9 percent (represented by columns (2)-(5)), the coefficient of the expenditure stock variable changes from 7.5 to 8, and is significantly different from zero at 10 percent level of significance. The coefficients of other control variables are very similar among the different models. This implies that contribution of expenditure stock towards productivity improves under the assumption of a more dynamic system where old knowledge is replaced quickly, while controlling for everything else. The coefficient increases as from 8.2 to 9.6, between 10 and 20 percent knowledge depreciation rate values. However this positive coefficient becomes statistically insignificant for higher rates of depreciation between 50 and 70 percent, and finally becomes negative for rates exceeding 80 percent, indicated in Appendix Table A1.

Knowledge stock in the 100 percent knowledge depreciation scenario is represented by current period expenditures on R&D and outreach; all previous expenditures become obsolete in terms of their effect. Regression results are reported in Column (9). We see that while coefficients for all other control variables remain similar to the depreciated knowledge cases, that for our expenditure stock becomes negative (-31.14) and significantly different from zero, at 5 percent

[12] 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.

level of significance. This implies that current expenditures reduce current total value of sales per acre by nearly $31. This negative coefficient could be capturing the allocation of higher value of resources for counties which have experienced low performance during that fiscal year, or cutbacks for a particular county that has performed well. Also, 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 have obtained. Therefore, consideration of only the current period expenditures on measuring the impact of R&D and outreach on productivity only tells us 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 in R&D and outreach; thereby providing a more complete understanding of long term impact of UCCE on county productivity.

Our previous results were based on the assumption that UCCE's research based knowledge equips farmers to modify their agricultural practices to adapt to disparities in temperature and precipitation. Now we include temperature and precipitation variables in our model (represented by model 4) and report the regression results in Table 3. Each column represents coefficients for each rate of depreciation, as in Table 2. We do not observe any significant coefficients for both the linear and quadratic terms for weighted mean county temperature and precipitation. However, controlling for temperature and precipitation, we find that the impact of UCCE expenditure stock on total value of sales per acre is slightly lower, in the range of $4-$8 per dollar expenditure by UCCE on R&D and outreach. Therefore, we find that UCCE expenditure stock does reduce any significant impact of weather on productivity through the dissemination of knowledge on adaptive measures to the farmers.

4.2 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 our theory that the impact of UCCE efforts on productivity varies across counties. From policy perspective this analysis is an important contribution to the literature. To achieve this we have made some modifications to our original model. The main empirical model remains unchanged; we include interaction terms between dummy variables representing each county and its UCCE expenditures into the old model. Regression coefficients for the 23[13] counties are reported in Table 4 for knowledge depreciation rates from 0 to 20 percent, and it includes only the coefficients for the county effects[14]. This model is estimated without including weather variables [15].

The first row in Table 4 reports the impact of UCCE in Alameda on total value of sales, which is negative for all our knowledge depreciation rates, and is statistically significant from zero for depreciation rates ranging from 7 to 20 percent. Fresno records the highest positive coefficient of UCCE expenditures stock; it varies from $124[16] to $230 addition to total value of sales per acre, for knowledge depreciation rates varying from 0 to 20 percent. The coefficient is statistically significant from zero at 1 percent level of significance. The second highest statistically significant impact is obtained for Tulare, and it varies between $48 to $100. San Bernardino has the next highest impact on total value of sales per acre, which ranges between $49 to $88.

The lowest positive impact is seen in Los Angeles county, ranging from $0.90 to $1.36. But this impact is statistically significant for δ=0.2. Kern, Monterey, San Joaquin, Stanislaus, and Ventura, which are among the top ten agricultural counties, have positive statistically significant impacts reported in columns (1)-(8). Alameda, Amador, Calaveras, Humboldt-Del Norte, Modoc and Siskiyou counties have negative coefficients for knowledge depreciation rates ranging from 0 to 20 percent. For Imperial county we observe a $9 to $10 increase in total value of sales for knowledge depreciation rates 0 and 10 percent respectively. For higher levels of knowledge depreciation rate, the value of the coefficients starts falling, and do not remain statistically significant from zero. 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, 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.

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 ten agricultural producers

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[13] 27 counties with statistically insignificant coefficients were removed from the analysis to minimize the loss of degrees of freedom.

[14] This is done due to space constraint.

[15] This is because of two reasons. First, we have not found any significant impact of mean temperature and precipitation on total value of sales per acre from our previous results. Secondly, estimation of weather variables on total value of sales per acre for each individual county would require the addition of at least 46-92 additional variables, for the linear and quadratic weather variables we included in equation 4. This would take away degrees of freedom to a large extent, and affect the accuracy of our results.

[16] Numbers are rounded.

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, dairy, and 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.

4.3. 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 research can be a substitute for the said input. For this exercise, we use the inputs that have been found to have a statistically significant positive impact on productivity, viz., 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):

$$MRTS_{1,2} = -\frac{MP_1}{MP_2} \qquad (7)$$

Using our regression coefficients in Table 2 we obtain the value of this ratio, which equals -0.00034 (-7.9/23096). This means that a dollar increment in UCCE expenditure stock per acre will lead to reduction in hired labor per acre by this fraction, keeping total value of sales per acre constant. For the next significant input, which is acres of chemicals applied as a share of total farmland acres, we find that MRTS equals -0.006 (-7.9/1248), representing the reduction in the input for a dollar increase in UCCE expenditure stock per acre farmland. Similar trends in substitution were reported in Goodhue et al. (2010) suggesting 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 expenditures per acre; it amounts to $49 ($6.2 $\times$7.9, where $6.2 is mean UCCE extension R&D expenditures and 7.9 is the mean value of the coefficient for UCCE expenditure stock[17]). Multiplying this $ value by mean farmland acres in our data set provides a total increase in value of sales amounting to $26,490,307 ($49$\times$540,618.5), on average per county. This provides some evidence of the scale of impact of UCCE expenditure stock on average county productivity. The same calculations for individual counties can provide a more in depth understanding of individual county level effect, for policy planning.

5. Summary, Conclusion and Policy Implications

We estimate the impact of University of California Cooperative Extension (UCCE) on county level agricultural productivity in California, using an agricultural production function model. Our analysis is aggregated to the county level because UCCE operates from county offices distributed across the state. We obtained data for UCCE budgets for all R&D and extension projects for 50 county offices statewide, for the years 1992 to 2012, and used them as proxies for R&D expenditures. Stock of knowledge produced through UCCE expenditures on R&D and outreach is modeled as a non-linear function of a stream of current and depreciated past expenditures, and used as our independent variable of interest. 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 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. We obtain temperature and precipitation data from NOAA, for all weather stations in California and calculate county levels means for our empirical analysis.

[17] This is calculated for knowledge depreciation rates ranging from 0 to 20 percent.

To estimate the impact of UCCE expenditures on R&D and outreach on productivity, we construct a stock of expenditures. For this we use current and 5 lagged values of UCCE expenditures, and a range of different depreciation rates. The intuition is that old knowledge depreciates over time, therefore older expenditures enter the model as a depreciated value. We analyze our agricultural production function 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 $5 to $10, for depreciation rates between 0 and 20 percent. For higher rates of depreciation of knowledge, 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 - 80%) levels of depreciation. For knowledge depreciation rate of 100 percent we find that the coefficient becomes negative (-$31) and this effect is statistically different from zero. This result likely captures the allocation of higher expenditures on counties which have reported lower performance during the year; or cutbacks for a particular county which is performing well. Therefore, our results are in agreement with the existing literature that 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 scope for improvement in research and outreach; introduction of new research-based knowledge and technology improve 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.

We test our hypothesis that UCCE equips farmers to adapt their production techniques according to weather variations, to minimize the impact of temperature and precipitation on productivity. Introducing weather variables in our model for each depreciation rate, we find that both linear and quadratic variables for weighted mean of county temperature and precipitation have no significant impact on total value of sales per acre. This result confirms our hypothesis that UCCE expenditure stock, which is utilized in research, outreach, and a highly developed irrigation monitoring system, absorbs the impact of weather on county level productivity.

Empirical results also include the impact of UCCE's R&D expenditure stock on individual counties. This is an important contribution to the literature, which has not adequately dealt with county level analysis of the state cooperative extension system before. Controlling for individual county and year fixed effects which may be driving productivity in that county, we find that some of the major agricultural counties in the state record high positive impacts of UCCE R&D expenditure stock. Out of the 50 counties in our study, we can see that UCCE R&D expenditures stock has a significant impact on 19 counties, of which we find a statistically significant negative impact on two counties - represented by the Humboldt-Del Norte county office. For the remaining counties the impact is not statistically different from zero. In terms of policy, these coefficients can be used as reference points for allocating budgets to different counties. Research and outreach 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 this paper.

A caveat of this paper is that spillover effects have not been included in the model. The empirical model assumes that there is no spillover; this effect can be incorporated in future work. This paper estimates a simplified version of the agricultural production function model to provide county level impact of UCCE expenditures on R&D and outreach on productivity, which can provide policy makers a reference point for policy decisions in California. Another caveat is the relatively short period of time (20 years), considered in our analysis. Longer time-series data would lead to higher values of benefits from our estimates.

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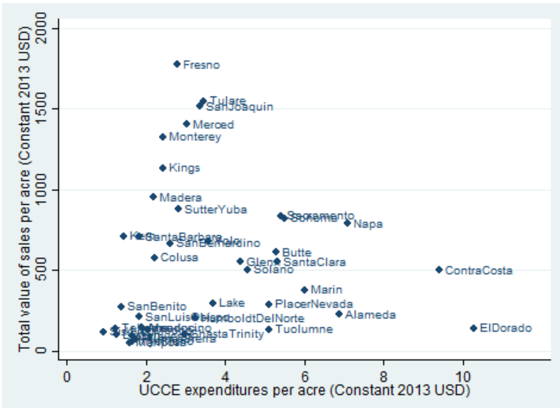
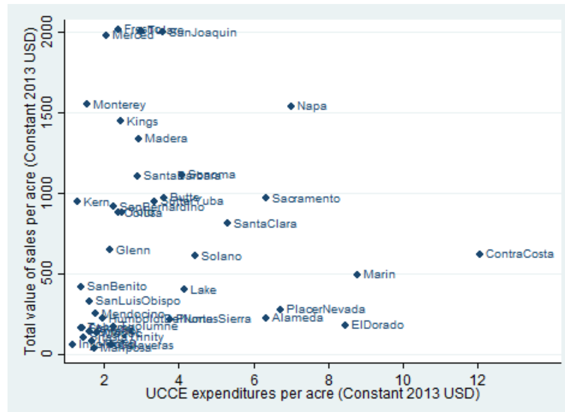
Figure 1. Total value of sales per acre and UCCE expenditures per acre (constant 2013 USD) for 1992 - 2012[18].

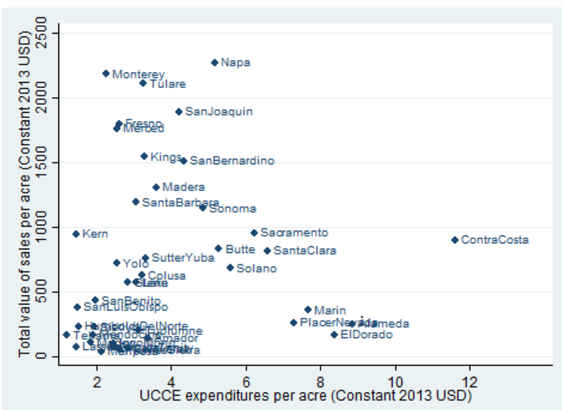
Panel (a): 1992



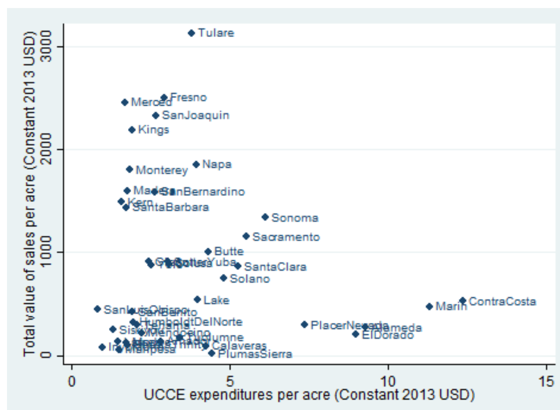
Panel (b): 1997



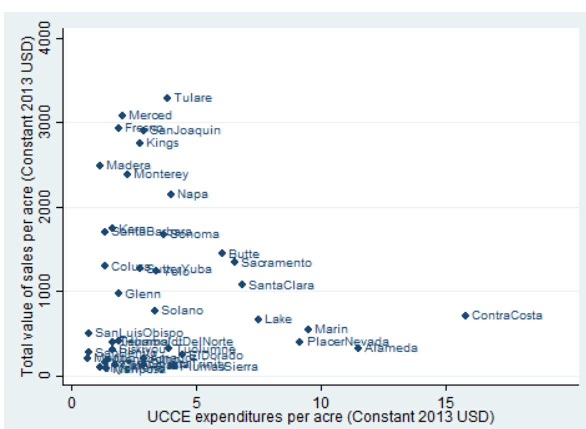
Panel (c): 2002



Panel (d): 2007



Panel (e): 2012

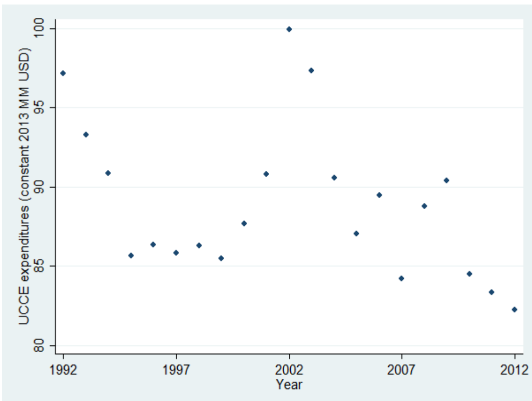


[18] Outliers are removed from the diagrams to improve interpretation of the names of counties.

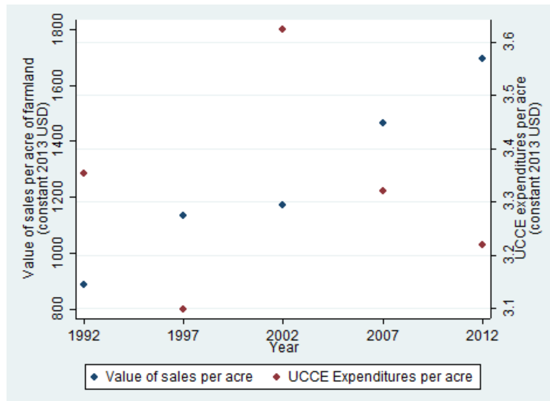
Figure 2. State-level UCCE expenditures, and their relationship with total value of sales per acre of farmland. Panel (a) Total expenditures by UCCE for 1992-2012 (constant 2013 million USD).

Panel (b) Total value of sales per acre of farmland and contemporaneous UCCE expenditures per acre for 1992-2012 (constant 2013 USD). Panel (c) Sum of current and last 5 year's UCCE expenditures per acre of farmland for 1992 – 2012 (constant 2013 thousand USD)

Panel (a)



Panel (b)



Panel (c)

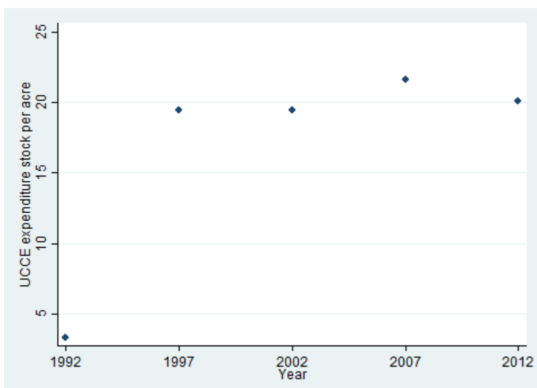


Table 1. Summary statistics

Variable	Observations	Mean	Standard Deviation	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
Average temperature (degree F)	250	59.85	4.80	46.70	74.58
Average precipitation (inch)	250	1.92	1.14	0.04	5.84

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

Table 2. Regression coefficients for models with UCCE expenditures stock expressed as sum of past expenditures undergoing depreciation in panel dataset.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	δ=0	δ =0.05	δ =0.07	δ =0.08	δ =0.09	δ =0.1	δ =0.15	δ =0.2	δ =1
R&D expenditure stock per acre	5.25*	7.49*	7.76*	7.90*	8.04*	8.19*	8.90*	9.62*	-31.14**
farmland	(2.71)	(3.74)	(3.90)	(3.99)	(4.08)	(4.16)	(4.63)	(5.12)	(19.37)
Acres harvested per acre of farmland	-631.9	-683.6	-688.5	-691.0	-693.6	-696.2	-709.7	-724.0	-580.8
	(2,380)	(2,358)	(2,357)	(2,357)	(2,357)	(2,356)	(2,355)	(2,354)	(1,990)
Hired labor per acre of farmland	23,262***	23,069***	23,070***	23,070***	23,070***	23,071***	23,075***	23,084***	25,089***
	(7,280)	(7,214)	(7,225)	(7,231)	(7,236)	(7,242)	(7,274)	(7,311)	(5,890)
Machinery per acre of farmland	28,253	27,949	27,985	28,005	28,027	28,050	28,193	28,390	46,645
	(33,349)	(33,028)	(33,034)	(33,037)	(33,040)	(33,044)	(33,065)	(33,090)	(29,349)
Chemicals per acre of farmland	1,248*	1,231*	1,230*	1,230*	1,230*	1,230*	1,230*	1,231*	1,407***
	(631.5)	(633.1)	(633.7)	(634.1)	(634.4)	(634.8)	(636.7)	(638.8)	(484.6)
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	-42.78	-43.04	-43.17	-43.30	-43.43	-44.13	-44.87	-34.04
	(34.83)	(33.90)	(34.05)	(34.14)	(34.22)	(34.31)	(34.79)	(35.35)	(36.18)
Constant	2,154	2,085	2,097	2,103	2,110	2,116	2,150	2,187	1,837
	(1,986)	(1,938)	(1,947)	(1,952)	(1,956)	(1,961)	(1,988)	(2,019)	(2,024)
Observations	249	249	249	249	249	249	249	249	249
R-squared	0.944	0.944	0.944	0.944	0.944	0.944	0.943	0.943	0.943
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. Regression coefficients for models including county mean temperature and precipitation, and UCCE expenditures stock expressed as sum of past expenditures undergoing depreciation in panel dataset.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	δ=0	δ=0.05	δ=0.07	δ=0.08	δ=0.09	δ=0.1	δ=0.15	δ=0.2	δ=1
R&D expenditure stock per acre	4.43*	6.35*	6.57*	6.67*	6.78*	6.89*	7.43*	7.94*	-33.43**
farmland	(2.47)	(3.44)	(3.59)	(3.66)	(3.74)	(3.82)	(4.23)	(4.67)	(13.46)
Acres harvested per acre of farmland	-580.3	-619.5	-624.0	-626.3	-628.6	-631.0	-643.4	-656.5	-542.4
	(2,209)	(2,191)	(2,190)	(2,190)	(2,190)	(2,190)	(2,189)	(2,189)	(2,243)
Hired labor per acre of farmland	23,263***	23,094***	23,098***	23,100***	23,101***	23,103***	23,116***	23,132***	24,893***
	(7,135)	(7,059)	(7,067)	(7,071)	(7,075)	(7,079)	(7,103)	(7,129)	(7,109)
Machinery per acre of farmland	29,991	29,690	29,742	29,770	29,800	29,831	30,018	30,265	48,192
	(33,829)	(33,567)	(33,575)	(33,578)	(33,582)	(33,587)	(33,609)	(33,634)	(34,510)
Chemicals per acre of farmland	1,196*	1,181*	1,181*	1,181*	1,181*	1,181*	1,180*	1,181*	1,340**
	(637.7)	(638.0)	(638.4)	(638.7)	(638.9)	(639.1)	(640.1)	(641.2)	(572.9)
Primary occupation	-1.20***	-1.20***	-1.20***	-1.20***	-1.20***	-1.20***	-1.20***	-1.20***	-1.16***
	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.25)
Average age	-46.24	-45.23	-45.47	-45.60	-45.73	-45.86	-46.55	-47.28	-37.45
	(34.93)	(33.90)	(34.06)	(34.15)	(34.23)	(34.32)	(34.81)	(35.37)	(37.00)
Mean annual temperature	215.6	220.0	220.3	220.4	220.5	220.7	221.4	222.1	184.7
	(354.0)	(354.1)	(353.9)	(353.7)	(353.6)	(353.4)	(352.7)	(351.8)	(346.3)
Mean annual precipitation	-322.9	-316.6	-319.0	-320.2	-321.5	-322.8	-329.9	-338.1	-471.2
	(298.1)	(296.8)	(296.8)	(296.8)	(296.8)	(296.8)	(296.9)	(297.1)	(291.4)
Mean annual temperature squared	-1.87	-1.91	-1.91	-1.91	-1.91	-1.912	-1.917	-1.921	-1.687
	(3.07)	(3.07)	(3.07)	(3.07)	(3.07)	(3.07)	(3.06)	(3.05)	(2.98)
Mean annual precipitation squared	38.18	37.61	37.90	38.05	38.21	38.37	39.22	40.19	50.77
	(41.11)	(41.07)	(41.09)	(41.10)	(41.11)	(41.12)	(41.17)	(41.24)	(39.96)
Constant	-3,442	-3,643	-3,637	-3,634	-3,631	-3,628	-3,609	-3,587	-2,258
	(10,593)	(10,550)	(10,546)	(10,543)	(10,541)	(10,538)	(10,525)	(10,511)	(10,325)
Observations	249	249	249	249	249	249	249	249	249
R-squared	0.945	0.945	0.945	0.945	0.945	0.945	0.945	0.944	0.945
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Coefficients of differential county level impacts of UCCE expenditures on total value of sales per acre, at different levels of knowledge depreciation.

VARIABLES	(1) δ =0	(2) δ =0.05	(3) δ =0.07	(4) δ =0.08	(5) δ =0.09	(6) δ =0.1	(7) δ =0.15	(8) δ =0.2
Alameda	-4.47	-6.28	-6.66*	-6.86*	-7.07*	-7.28*	-8.45*	-9.82*
Amador	-20.88**	-28.99**	-30.38**	-31.10**	-31.84**	-32.59**	-36.60**	-41.02**
Calaveras	-15.87**	-20.70**	-21.62**	-22.09**	-22.58**	-23.07**	-25.63**	-28.38**
Fresno	123.63***	167.42***	174.84***	178.64***	182.43***	186.42***	207.35***	229.98***
Humboldt-Del Norte	-30.38***	-52.39***	-56.25***	-58.32**	-60.50***	-62.77***	-75.96***	-92.97***
Imperial	9.44**	10.20*	10.28	10.3	10.31	10.32	10.18	9.64
Kern	39.88***	57.18***	59.91***	61.34***	62.80***	64.31***	72.51***	81.96***
Los Angeles	0.90	1.07	1.11	1.13	1.14	1.16	1.26	1.36*
Modoc	-31.38***	-38.35**	-39.71**	-40.38**	-41.06**	-41.72***	-44.85**	-47.37*
Monterey	30.23**	48.16**	50.90***	52.35***	53.84***	55.40***	64.10***	74.63***
Napa	15.12***	21.10***	22.02***	22.49***	22.98***	23.46***	26.03***	28.78***
Orange	8.27***	9.66***	9.84***	9.92***	9.99***	10.05***	10.20***	9.95***
San Bernardino	49.17***	64.00***	66.72***	68.13***	69.56***	71.04***	78.90***	87.67***
San Diego	5.78***	8.05***	8.47***	8.69***	8.92***	9.15***	10.45***	11.99***
San Francisco-San Mateo	3.25***	5.66***	5.89***	6.00***	6.11***	6.23***	6.82***	7.44***
San Joaquin	16.00***	24.76***	25.84***	26.40***	26.96***	27.54***	30.57***	33.79***
Santa Clara	0.02	-0.04	-0.14	-0.18	-0.24	-0.29	-0.62	-1.05
Santa Cruz	10.31***	18.32***	19.68***	20.41***	21.17***	21.98***	26.69***	32.79***
Siskiyou	-33.95***	-42.95***	-45.03***	-46.10***	-47.21***	-48.35***	-54.45***	-61.34***
Sonoma	21.16***	30.11***	31.55***	32.29***	33.05***	33.83***	38.01***	42.69***
Stanislaus	12.98**	17.78**	18.27**	18.51**	18.73**	18.96**	19.90**	20.35*
Tulare	47.68***	69.36***	72.76***	74.53***	76.35***	78.22***	88.40***	100.08***
Ventura	9.69*	13.89**	14.58**	14.94**	15.30**	15.69**	17.80***	20.30**

*** p<0.01, ** p<0.05, * p<0.1

Appendix Tables

A1. OLS regression results for cross section and panel data under the assumption of depreciation rates 50, 70and 80 percent.

VARIABLES	(1) δ=0.5	(2) δ=0.7	(3) δ=0.8
R&D expenditure stock per acre farmland	10.49	0.54	-8.91
	(7.53)	(7.34)	(8.58)
Acres harvested per acre of farmland	-803.1	-780.3	-727.7
	(2,359)	(2,389)	(2,409)
Hired labor per acre	23,350***	23,945***	24,352***
	(7,618)	(7,747)	(7,703)
Machinery per acre	31,751	37,257	40,666
	(33,328)	(33,756)	(34,203)
Chemicals per acre	1,256*	1,311**	1,346**
	(650.3)	(640.6)	(624.5)
Primary occupation	-1.17***	-1.15***	-1.15***
	(0.25)	(0.25)	(0.25)
Average age	-48.78	-46.97	-43.64
	(40.42)	(43.18)	(42.85)
Constant	2,398	2,360	2,234
	(2,295)	(2,433)	(2,404)
Observations	249	249	249
R-squared	0.941	0.940	0.941
County FE	YES	YES	YES
Year FE	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.

A2. Correlation between total value of sales per acre and UCCE expenditures for the census years.

	UCCE expenditures per acre of farmland				
	1992	1997	2002	2007	2012
Total value of sales per acre of farmland	0.81	0.66	0.70	0.53	0.25