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A Knowledge Production Function of Agricultural Research and Extension: The Case of the University of California Cooperative Extension

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Summary:

We estimate the impact of various research inputs on the production of research-based knowledge by the University of California Cooperative Extension (UCCE). We formulate a conceptual framework to understand the relationship between the research inputs employed by UCCE, and the produced knowledge. We developed an index of knowledge based on a weighted average of the various modes through which knowledge is produced by UCCE's research, for all counties under its jurisdiction, in the state during 2007-2013. Empirical results indicate significant positive impacts of research inputs on the production of knowledge. Research knowledge such as number of research positions, measured as full time employee - FTE, level of salary per researcher, indicating seniority and status, and investment in research infrastructure per research position, were found positive and significant. Our models suggest diminishing marginal returns to research infrastructure, and a linear relationship for number of FTE and salary per FTE with knowledge production.

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A Knowledge Production Function of Agricultural Research and Extension: The Case of the University of California Cooperative Extension

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Abstract

We estimate the impact of various research inputs on the production of research-based knowledge by the University of California Cooperative Extension (UCCE). We formulate a conceptual framework to understand the relationship between the research inputs employed by UCCE, and the produced knowledge. We developed an index of knowledge based on a weighted average of the various modes through which knowledge is produced by UCCE's research, for all counties under its jurisdiction, in the state during 2007-2013. Empirical results indicate significant positive impacts of research inputs on the production of knowledge. Research knowledge such as number of research positions, measured as full time employee - FTE, level of salary per researcher, indicating seniority and status, and investment in research infrastructure per research position, were found positive and significant. Our models suggest diminishing marginal returns to research infrastructure, and a linear relationship for number of FTE and salary per FTE with knowledge production. (150 words)

Keywords: Knowledge production function, cooperative extension, agricultural R&D, University of California Cooperative Extension.

JEL Classifications: C23, Q1, Q10, Q16

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A Knowledge Production Function of Agricultural Research and Extension: The Case of the University of California Cooperative Extension

1. Introduction

"Technological innovation has become a crucial factor for competitiveness."[1] The measurement of the capacity to invent and innovate has become extremely important, especially in the agricultural sector due to scarcity of natural resources such as land and water on one hand, and demand for food driven by population growth on the other hand. According to Food and Agricultural Organization (FAO) estimates[2], global population is expected to grow by over a third, or 2.3 billion people, between 2009 and 2050. Agricultural productivity would have to increase by about 70 percent to feed the global population of 9.1 billion people over this period. Arable land would need to increase by 70 million ha, with considerable pressure on renewable water resources for irrigation. Efficiency in agricultural practices and resource usage are the suggested prescriptions to ensure sustainable agricultural production. Sands et al. (2014) also predict net positive improvements in global agricultural production in the year 2050, in a simulated scenario of rising population and low agricultural productivity growth. While such studies are reassuring, it becomes imperative to ensure continuous research and development in agriculture; to not only have a comprehensive understanding of how to sustain current rate of productivity growth but also increase it in order to counter both population growth and natural resource scarcity in the future. Hence, the quantification of the process of creation of agricultural knowledge in the research process is the focus of this paper.

We focus on the production of research-based agricultural knowledge by the University of California Cooperative Extension (UCCE). This publicly funded research and extension system has offices across all counties within the state if California. We analyze the nature of the input-output relationship between the research inputs invested by UCCE in R&D and outreach, and the knowledge produced and disseminated by UCCE.

The University of California Cooperative Extension (UCCE) was set up a century ago with the purpose of educating the citizens about agriculture, home economics, mechanical arts and other

1Buesa, Heijs, and Baumert (2010)

2 http://www.fao.org/fileadmin/templates/wsfs/docs/Issues_papers/HLEF2050_Global_Agriculture.pdf

practical professions[3]. Through the course of almost a century since the Smith-Lever Act of 1914, the UC Cooperative Extension has grown into an 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, consumers, who then adopt and adapt it to improve productivity, and income. Today the Extension works in six major areas[4], viz., *Agriculture, 4-H Youth Development, Natural Resources, Leadership Development, Family and Consumer Sciences,* and *Community and Economic Development.*

The literature suggests that agriculture-related R&D inputs result in the production of knowledge, which upon application leads to improvement in productivity in the agricultural sector. Alston et al. (1998; 2008), Birkhaeuser et al. (1991), and Evenson (2001) estimate the impact of R&D and extension related expenditures on agricultural productivity. The underlying theory is that expenditures made towards R&D and outreach impact productivity, and that impact of research expenditures is differential; old expenditures have a lower impact on current productivity. Evenson (2001) and Birkhaeuser et al. (1991) report positive impacts of both R&D as well as cooperative extensions on productivity, for studies from around the world. While these studies provide strong evidence of a long-term impact of R&D related expenditure, and impact of farmer-extension agent contacts on productivity, there is a gap in our understanding of how well these proxies for agricultural knowledge represent actual knowledge produced. This is understandable, since measurement of knowledge produced from investments in R&D is conceptually and computationally complicated.

Griliches (1998) discusses the issues of the measurement of knowledge production, between public and private sector investments in R&D. He claims that patents are a good approximation of knowledge and innovation, especially because of the commercial value attached to it. An industry or a firm likes to file for patents to have sole right on its invention, and get paid for its use by others. Pavitt (1985) mentions that patents are good proxy measures of innovative activities. Other studies (Fritsch; 2002, Abdih and Joutz; 2005, Czarnitzki, Kraft, and Thorwarth; 2008, Ponds, Oort, and Frenken; 2009, and Buesa, Heijs, and Baumert; 2010) have used patents

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

[4]http://www.csrees.usda.gov/qlinks/extension.html#today

as proxies for knowledge production. Data on patents are well documented in the U.S. as well as the rest of the world, and are easily obtainable without the hassle of conversion of units. In the industrial sector, knowledge produced through research is mostly owned as private property by the innovating firm because of the related commercial incentive of private property ownership. This makes patents the most appropriate proxy variable for knowledge production function analysis, in the case of private sector research.

However, publicly funded research and especially agricultural research, creates knowledge most of which is publicly available. Pardey (1987) and Dinar (1991) use publications as the dependent variable as a proxy to knowledge production. Publications are more prevalent in case of public research agencies, where research results are typically published in journals. Dinar (1991) uses peer-reviewed journal publications in different fields as the dependent variable for his study on the agricultural research system in Israel. In case of public agricultural research systems in the U.S. as for Pardey (1987), publications have been chosen over a number of other variables including patented and non-patented output like mechanical innovations processes or new biological material, books, station (State Agricultural Experiment Station, or SAES) bulletins, newsletters, etc. Publications are considered to capture the knowledge output of a station completely because it establishes intellectual property rights of the researchers over their work, which in turn affect their salary scale, promotion rate, and tenure status. Link (1982) analyzes the determinants of inter-farm differences on the composition of R&D spending, namely basic and applied R&D. He regresses these R&D components on profits, diversification, ownership structure and subsidies. Jaffe (1989) finds significant positive impact of university research on corporate patents for a number of technical areas such as drugs and medical technology, and electronics, optics and nuclear technology for U.S states. The literature on the topic leads us to two main observations: (i) there is a dearth of papers that deals with the analysis of the knowledge production function or the study of impact of production inputs on knowledge produced; and (ii) the choice of variables representing knowledge produced through investments in R&D paints a partial picture of the true process. There is little attempt to compute a comprehensive knowledge production variable which captures knowledge produced through all avenues.

UCCE follows an input-output framework for research, which involves utilization of research inputs, such as manpower and infrastructure, for the production of knowledge to be disseminated to potential clientele from a variety of different sectors. This knowledge is produced through basic and applied research, and extension work, which are targeted to address needs at county level clientele groups. Agricultural knowledge that is generated by UCCE is public in nature, and is freely available to all. Because of this, it seems appropriate to use various types of peer-reviewed publications by advisors as the representative variable for knowledge. But publications are only a part of the total knowledge produced; there are other modes by which knowledge is produced and disseminated by UCCE. These need to be incorporated into the analysis to capture a more complete representation of the generated knowledge. To achieve this, we collected data on eleven different modes by which UCCE produces knowledge, all of which are aggregated to the county level, to create a knowledge index that captures all UCCE knowledge produced.

This paper contributes to the literature in a couple of ways that sets it apart from similar endeavors. It estimates the impact of research inputs on the production of knowledge solely by UCCE, which is the biggest statewide public agricultural research and extension system, and second, it develops and uses a weighted average value of knowledge including a number of different components of knowledge produced.

The remainder of the paper is organized as follows. Section 2 develops the econometric methodology. Section 3 describes the data and variable creation. Section 4 reports the empirical results. Conclusion and policy implications are presented in section 5.

2. Analytical Framework

The basic structure of the knowledge production function is similar to a standard production function where the output is knowledge produced in county *i* at time *t;* it is a function of three identified input variables: full time equivalent (FTE) extension positions, expenditures on salaries per unit FTE, and expenditures on infrastructure per unit FTE. Therefore, the general form of the model is:

$$K_{it} = f(FTE_{it}, S_{it}, I_{it}) \qquad (1)$$

where i = 1, 2..., N county offices, t = t_1, t_2, …, t_n. K is knowledge produced from expenditures made by UCCE. *FTE* is the Full Time Equivalent Employment advisor positions. S is expenditures on salaries, per unit FTE. I is 'non-salary related' expenditures on infrastructure, including benefits, travel expenses, and county extension programs.

The following econometric model that we estimate includes natural logs of both the independent and dependent variables:

$$lnK_{it} = \alpha + \beta lnFTE_{it} + \gamma lnS_{it} + \delta lnI_{it} + \theta(lnI_{it})^2 + \rho D_i + \varphi T_t + \varepsilon_{it} \quad (2)$$

where ε_{it} is the error term, i is an index for all county offices and time 2007-2013. K_{it}, FTE_{it}, S_{it}, I_{it}, are defined the same way as for equation (1); D_i is the control variable for county fixed effects, and T_t is the control variable for year fixed effects.

Dichotomous variables representing county fixed effects are introduced in the model to control for factors that are common to a county, and possibly impact productivity. Year fixed effects can control for random shocks, e.g., budget surplus leading to a recruitment of more skilled advisors in a particular year, which may have led to larger number of total knowledge produced across all counties in a single year.

The model includes a non-linear term for investments in infrastructure. This is included to capture possible diminishing marginal returns to infrastructure. Expenditure on infrastructure can be beneficial to knowledge production, but after a certain degree of provision the marginal effect diminishes. It makes little sense to keep building laboratories and offices if there are no researchers, or staff to fill them. To test this hypothesis, the square term for log of infrastructures was included. The choice of the log-log model for the empirical analysis is to facilitate the computation of output elasticity for each of the inputs of production. In case of linear relationships between inputs and output, the elasticity can be obtained from the value of the regression coefficient. For non-linear relationships, the computation is slightly less straightforward.

We calculate output elasticities for each of our inputs from our empirical model in equation (2). The elasticities of knowledge production are:

$$\frac{dK/dFTE}{K/FTE} = \beta \quad (3)$$

$$\frac{dK/dS}{K/S} = \gamma \quad (4)$$

$$\frac{dK/dI}{K/I} = \delta + 2\theta(lnI) \quad (5)$$

Equation (5) is dependent on the level of investments in infrastructures. For the output elasticity calculations, we use regression coefficients reported in Section 3.

We also estimate equation (2) including a linear time trend instead of year fixed effects. This is to de-trend both the dependent variable as well as the independent variables (Enders 2010; Wooldridge 2013), and to capture un-modeled effects including UCCE R&D and outreach efforts, which may impact the knowledge variable. Failure to deal with two uncorrelated time-series variables trending over time in the same direction can lead to spurious results. The following section describes the data used for the study.

3. Data

University of California Agricultural and Natural Resource Division (UCANR) headquarters in Oakland, California, is the source of data for the analysis in this paper. We collected annual budget data from their database for all UCCE county offices for the period of 2007 to 2013.[5] Our data set includes complete data for 7 years for 47 county offices, which serve the 58 counties in California. Some county offices serve more than one county, such as Central Sierra, which serves the counties of Amador, Calaveras, El Dorado and Tuolumne. There are 6 other groups of two counties each, which are served by a single county office, such as Inyo and Mono, San Francisco and San Mateo, Plumas and Sierra, Placer and Nevada, Shasta and Trinity, and finally Sutter and Yuba.

[5] Data on UCCE budgets was obtained from 1992 -2013, but data on all other variables was available only for 2007-2013.

Upon comparing older UCCE budget data with real expenditures, we found that they follow similar time trends for each county office and could be used as proxies for expenditures. This data was converted into constant 2013 US dollars, using GDP Deflator data from the World Bank database and is presented as such from hereafter.[6] Henceforth, we will refer to the UCCE budget as expenditures, to avoid ambiguity. The expenditures made by UCCE are shown in panel (d) of Figure (1). There is evidence of impact of the 2009-2010 recession on investments in 2010, which goes down from over $90 million to less than $85 million. From 2010 onwards, we observe a steady decline in annual UCCE expenditures, to about $76 million in 2013. In 2007, the county offices that record some of the highest amounts of overall expenditures include Fresno, Tulare, San Diego, Humboldt-Del Norte, San Joaquin, Ventura and Kern, in declining order. In 2013 we notice that leading counties in terms of overall expenditures are San Diego, Tulare, Kern, Plumas-Sierra, and San Francisco and San Mateo.

Data on salaries of advisors employed in each county office is collected from UCCE database as well. Expenditure on infrastructure is the amount remaining from the budget, after subtracting total expenditures on salaries for the counties. These expenditures capture non-salary related expenditures, including benefits and travel provisions for county advisors, along with various expenditures on research and outreach programs taken up by the county offices. Full time equivalent (FTE) employment data is obtained for advisors employed by each county office. We observe an overall fall in both advisor FTE and advisor salaries, as represented in panel (a), Figure 1. After 2010, both FTE and expenditures on salaries show consistent decline. We observe (panel (c), Figure 1) an overall declining trend in expenditures on infrastructure, with a fall of about $5 million between 2009 and 2010. This could be the effect of the 2009-2010 recession, which also led to a fall in overall expenditures during that period. Panel (d) reflects the decline in total expenditures that include both salaries and non-salary infrastructure related expenditures.

The outcome variable in our empirical analysis, knowledge, is created using data on a number of component variables. UCANR records data on a variety of methods in which knowledge, produced through investments in research and infrastructure, is disseminated. We use knowledge produced and knowledge disseminated interchangeably because all knowledge produced by

[6] http://data.worldbank.org/

UCCE is public good, and is disseminated. Hence, the methods of dissemination capture knowledge produced. These methods are categorized into three main knowledge groups. The first group includes data on classes, workshops, demonstrations, individual consultations, meetings or group discussions, educational presentations at meetings, and all other kinds of direct extension activities. The variable is named *direct contact* knowledge, and it includes all counts of knowledge dissemination from direct contact with growers. The second group is named *indirect contact* knowledge, and it includes counts of knowledge disseminated through indirect contact with possible clients via newsletters published and websites managed by UCANR, television, radio programs or public service announcements, social marketing methods, other mass media efforts of knowledge dissemination, and other indirect extension efforts, including those through collaboration with other agencies. The last category is named *research publication and other creative activity* related knowledge. This category includes counts of basic, applied or development research projects, program evaluation research projects, needs assessment research projects, educational products created via video and other digital media, curricula, and manuals created for education purposes. We also include publications in peer-reviewed journals in this category. The above data on knowledge is recorded as counts. The input variables are not available in a way such that we can categorize them into issues related to agriculture only. Hence, to avoid overestimation issues, we include knowledge produced for all programs undertaken by UCCE for the period of study.

Using the data on all knowledge categories we generate an index of knowledge as a weighted average of all the categories[7]. We assign weights to each category, based on relative importance of each kind of knowledge variable in terms of effectiveness. For this, we sent an electronic survey (Appendix Table A1) to the county directors of all UCCE county offices in California. In the survey, we indicated the three above-mentioned broad categories of knowledge production, with a number of subcategories. Respondents provided percentage weights for each broad category such that the sum would add up to 100. Within each broad category respondents

[7] The equation for computing the knowledge index is the following:

$$K_{it} = (\beta_1(\theta_{11}k_{11} + \theta_{12}k_{12} + \theta_{13}k_{13}) + \beta_2(\theta_{21}k_{21} + \theta_{22}k_{22} + \theta_{23}k_{23} + \theta_{24}k_{24}) + \beta_3(\theta_{31}k_{31} + \theta_{32}k_{32} + \theta_{33}k_{33} + \theta_{34}k_{34}))_{it}$$

In the above equation, i = 1, 2, ….47 counties, and t = 2007, 2008…., 2013, years.
Beta values stand for the weights for each of the three broad categories; theta values stand for the weights for the subcategories. K variables represent knowledge, with the upper-case ‘k’ representing overall knowledge, and the lower-case representing the subcategories.

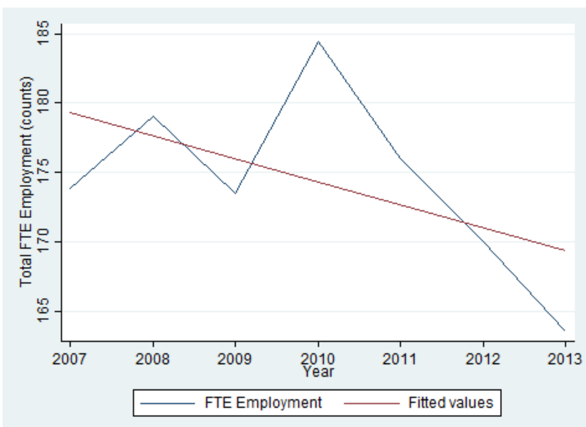
indicated percentage weights for each of the subcategories such that the sum of these weights also equals 100. We obtained 10 replies after two rounds of survey of the county directors, and created weights from the survey results. Two rounds of completed surveys indicate that direct contact with farmers is the most important (50%), followed by indirect contact (27%), and own research and publications (23%), in terms of their impact on agricultural productivity. Among the subgroups, applied research projects receive the highest weight (49%), followed by individual consultations (42%), and group interactions (38%), within their respective groups.

From the data collected on knowledge production variables we identify 7 different Federal Planned Programs (FPP): *Climate Change*, *Healthy Families and Communities*, *Sustainable Food Systems, Water Quality, Quantity, and Security, Sustainable Energy, Endemic and Invasive Pests and Diseases*, and *Sustainable Natural Ecosystems*. Climate Change was dropped from the official FPP categories from fiscal year 2013. Knowledge produced through indirect methods of contact is the most popular means of knowledge production, due to the comparatively lower cost of dissemination and wider reach to possible clientele, followed by direct contact. Direct contact methods are costlier than the former, and has a more limited reach. Research projects and peer-reviewed publications and the knowledge produced through them are also available for the public, but perhaps cater to a smaller audience compared to the other two methods. However, they are certainly a significant component in the direct interactions of the specialists and county advisors with farmers.

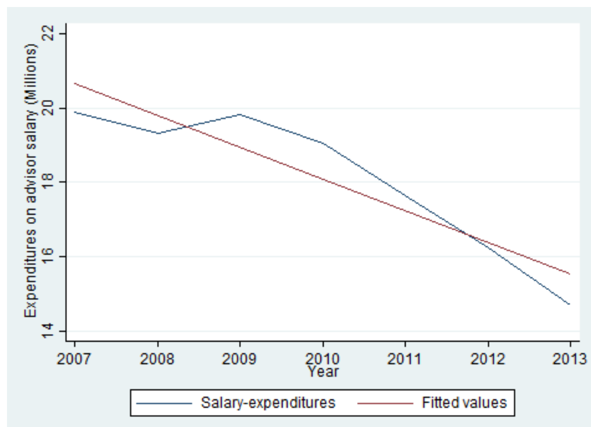
Over the period of 2007-2013 we observe that all knowledge production declined as is illustrated in Figure 2. Total knowledge produced in each of direct contact, indirect contact, and publication and research project methods of production have declined over time. Total number of counts of knowledge produced through all direct contact methods rose by 43 per cent, from 15,059 in 2007 to 21,479 in 2011, but thereafter it keeps falling till it reaches a total count of 8282 in 2013, which is a 61 per cent decrease compared to 2011. Knowledge produced through different methods of indirect contacts with growers, starts from 259,065 in 2007, and peaks at 405,386 in 2009, before falling down to nearly 43 thousand counts per year in 2010. In 2013, the recorded number is 100,919, which is equivalent to a 61 percent reduction from the original levels in 2007. Research projects and peer-reviewed journal publications went down from 3,349 in 2007 to 506 in 2013, which is a percentage decline of nearly 85 percent of the 2007 value.

Figure 1. Panel (a): Annual UCCE advisor FTE (counts), Panel (b): Annual expenditures for UCCE advisor salaries (Constant 2013 Million USD), Panel (c): Annual expenditures for UCCE infrastructures and programs (Constant 2013 Million USD), and Panel (d): Annual total expenditures of UCCE (Constant 2013 Million USD).

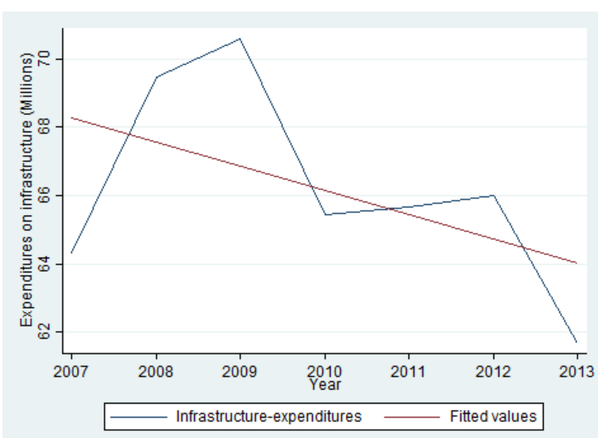
Panel (a)



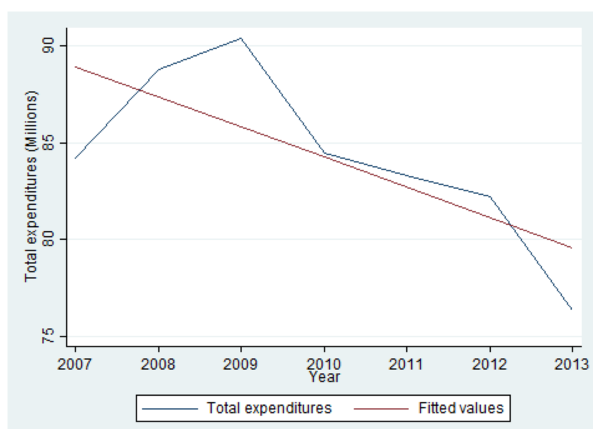
Panel (b)



Panel (c)



Panel (d)



Among all the counties, San Diego records the highest average (over time) count of knowledge production from direct methods, at 1714[8] (maximum 2817, minimum 470), and Madera the lowest, at 3 (maximum 17, minimum 0). San Joaquin has the highest average count of knowledge production from indirect contact method at 49,225 (maximum 262,205, minimum 0), and Madera the lowest, at 0. San Luis Obispo has the highest value of average knowledge production through publications and research projects, at 308 (maximum 1890, minimum 27), and Mariposa the lowest, at 1 (maximum 4, minimum 0).

Figure 2. Panel (a): Counts of direct methods of knowledge production Panel (b): Counts of Indirect methods of knowledge production Panel (c): Counts of research and creative activity methods of knowledge production

Panel (a) Panel (b) Panel (c)

We observe (Appendix Table A6) that each of the three defined categories of knowledge variables have high variability. It will be interesting to know what causes such a large variation; what factors play a role in the decision making process on the number of knowledge production activities. For this paper, we observe from the data set that there is an overall falling trend in both inputs of knowledge production, such as county level FTE, expenditures on salaries per unit FTE, expenditures on infrastructure per unit FTE, as well as output, i.e., weighted knowledge produced from all three identified sources. In the next section, we report the results of our econometric estimates of the knowledge production function.

[8] All numbers are rounded off for ease of interpretation.

4. Results

Summary statistics of the variables in our analysis are reported in Table 1; we observe high levels of dispersion in the distribution of some of the knowledge variables. For example, while there is at least one county which has produced 0 newsletters, the maximum number of newsletters sent out by another county equals 262,174 (San Joaquin county in 2009). San Joaquin has the highest mean knowledge index value over 2007-2013 at 3,503; nearly 9.8 times the sample mean of 359. This county has employed a mean FTE of 5.9, which is 59 percent higher than the sample mean of 3.7. Expenditure on salaries per FTE ($124,522) for this county is 2.5 percent higher, and infrastructure per FTE ($530,034) is 19 percent higher than their sample means. Madera county has the lowest average knowledge index value in our data set, which is nearly 1, and less than the sample mean by more than 358 percent. Madera county's mean FTE value is 1.3, less than the sample mean by 64 percent, mean expenditures on salaries per FTE ($195,455**)** is greater than overall average by 61 percent, and expenditures on infrastructure per FTE ($535,444) greater than overall average by 20 percent.

From county level descriptive statistics, it is evident that knowledge creation strategies vary significantly among counties resulting from size and nature of the agricultural activity. Between San Joaquin and Madera, the highest and lowest knowledge producing counties (in absolute terms), there is a 100 percent decrease in knowledge produced. Mean advisor FTE number in San Joaquin is 353 percent higher than that in Madera; with 36 percent lower expenditures on salaries per unit FTE, and a 1 percent lower expenditure on infrastructure per FTE, compared to Madera county.

We observe high levels of knowledge production in some counties that are important agricultural producers, like San Joaquin, which is one of the leading producers of fruits and nuts, and dairy. Merced has the second highest rate of knowledge production that equals 2,308, followed by Kings county (2,042), which is also among the top ten agricultural counties for cattle and dairy, vegetables and cotton. Other top agriculturally productive counties like Fresno, Kern, Tulare have higher (9, 8.9, and 9.1 respectively) number of FTE advisors compared to our overall mean, but are not among the highest average knowledge producers.

The knowledge index, the weighted average of counts of the component variables, has been declining for the period of our study, as seen in Figure 3. The average value of log (knowledge index) has gone down from about 3.9 to about 2.75 over the period of 2007 - 2013, which reflects a 68 percent decline in the knowledge index. With these observations, it is important to know how our inputs impact average knowledge produced, and how these declining trends in inputs may impact knowledge production.

Table 1. Summary Statistics[9]

Variable	Observations	Mean	Std. Dev.	Min	Max
FTE	329	3.71	2.49	.2	12.1
Salary/FTE	329	121,501.9	149,510.7	2066.23	2,656,400 [10]
Infrastructure/FTE	329	444,873.1	254,058.2	51,563.44	2,432,511
Individual Consultation	329	105.72	277.10	0	2682
Group Interaction	329	127.77	468.31	0	5051
Other Direct	329	57.75	187.22	0	2374
Newsletters	329	4,269.51	20,887.01	0	262,174
Websites	329	5.69	10.01	0	61
TV & Radio	329	25.39	125.08	0	1003
Other Indirect	329	106.13	911.15	0	12002
Publications	329	13.43	17.95	0	107
Basic Research	329	0.51	1.25	0	12
Applied Research	329	6.40	6.61	0	45
Other Research	329	10.82	103.52	0	1849
Knowledge Index (count)	329	358.63	1464.80	0	18,179.18

Note: All knowledge production variables, and FTE are computed as counts. Knowledge index can also be interpreted as a county variable, being the weighted average of component knowledge production variables. Expenditures in salaries and infrastructure are expressed in constant 2013 USD.

[9] Summary statistics indicate 0 values for some of the knowledge production subcategories. When we construct the knowledge index, we obtain 0 values for 30 observations. STATA output regards natural log transformations of 0 values as 'missing values', and drops them from the regression. But the 0 value cases imply no knowledge production, and provide important information as far the analysis of impact of inputs on knowledge production is concerned; so we keep them in the sample, by recoding them as 0 values.

[10] According to our data the real expenditures on total salaries in San Francisco-San Mateo counties for the year 2013 is $531,280. The advisor FTE for this year is 20 percent. The normalization of the salary expenditure by the FTE leads us to this number.

Figure 3. Annual mean ln (Knowledge Index)

Table 2 reports the regression results of equation (2) including two different models. Column (1) reports the results for the case where we include county and year level dummy variables to control for any factors that remain fixed across counties or years, which may impact the dependent variable. The second version of the model (Column (2)) includes a time trend instead of time fixed effects.

Table 2. Regression results with log weighted average of knowledge (knowledge index) as dependent variable. [11]

Model	(1)	(2)
Dependent VARIABLE	ln (Average Knowledge)	ln (Average Knowledge)
ln(FTE)	1.10**	1.07**
	(0.51)	(0.51)
ln(Salary/FTE)	0.86***	0.87***
	(0.23)	(0.23)
ln(Infrastructure/FTE)	14.17**	14.25**
	(6.86)	(6.71)
ln(Infrastructure/FTE) squared	-0.56**	-0.56**
	(0.27)	(0.27)
Constant	-94.58**	237.6**
	(43.99)	(98.97)
Observations	329	329
R-squared	0.664	0.662
AIC	1259.61	1250.83
County FE	YES	YES
Year FE	YES	NO
Time Trend	NO	YES
F-stat	27.67***	30.97***

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

We obtain statistically significant coefficients for all the input variables for both versions of our model, reported in columns (1), and (2) (Model (1) and (2). A percentage rise in FTE impacts knowledge production positively by nearly 1.1 percent. A 1 percent rise in expenditures on

[11] We estimate equation (2) using the same inputs of production but each of the 3 broad knowledge categories and then each sub category as the dependent variable. Results are shown in the Appendix.

salaries per unit FTE increases knowledge production by 0.86 percent. The coefficient estimate for expenditures on infrastructures per unit FTE is positive and the coefficient estimate of the quadratic term is negative, supporting the theory of diminishing marginal returns to expenditures in infrastructure per FTE employee. In Model (2), we control for county level fixed effects by introducing county dummy variables. Here, we de-trend the dependent variable as well as the independent variables by including a time trend variable in the model. We report robust standard errors in the parentheses. Coefficient estimates for both the models are comparable to each other.

From Table 2, we compute the elasticities of production. These are reported in Table 3 below.

Table 3. Elasticities of production of weighted average knowledge.

Output Elasticity	Model (1)	Model (2)
$\frac{dK/dFTE}{K/FTE} = \beta$	1.10	1.07
$\frac{dK/dS}{K/S} = \gamma$	0.86	0.87
$\frac{dK/dI}{K/I} = \delta + 2\,\theta\,(\ln I)$	-0.39	-0.31

The elasticity of production of knowledge with respect to FTE varies from 1.066 to 1.104, across the two models we estimated. A 1 percent increase in FTE leads to a 1.1 percent increase in average knowledge produced. Similarly, a 1 percent increase in expenditures on salaries per unit FTE would bring about a 0.87 percent increment in average knowledge produced by UCCE. The elasticity for expenditures on infrastructures per FTE for both models are calculated at the sample mean of this variable (444,873.1), using equation 5, as reported in Table 3. This value is negative, both in Model (1), and Model (2). Due to diminishing marginal returns, relationship between this input and knowledge produced is concave, and the elasticity therefore depends upon the value of expenditures at which it is calculated. We compute the value of expenditures on infrastructure per unit FTE that corresponds to the turning point of the production function from a positive to negatively slope; this value equals $312,320.[12] Expenditures on infrastructure per FTE less than this amount will yield a positive output elasticity; higher values will yield negative output elasticity, as is the case when we use the mean value.

We observe that FTE is the most important input in the knowledge production process, with an elasticity greater than 1. The advisor FTE employed by the county offices are engaged in various kinds of research and outreach operations, and are the most important factor in the process of knowledge production. Dinar (1991) finds similar evidence of significant positive marginal product of senior researchers on production of knowledge for the public agricultural research system in Israel. Expenditures on salaries act as incentive system to make the current advisor FTE more productive, which enhances productivity, as is indicated by our results. Expenditures on infrastructure have positive impact on knowledge production before the threshold level is reached, beyond which the impact becomes negative.

5. Conclusion and Policy Implications

We have estimated the contemporaneous impact of UC Cooperative Extension on the production of knowledge, through research and extension work that is conducted over various California counties. Available data on R&D expenditures and knowledge products is used to construct a unique data set for 7 years spanning from 2007-2013, containing information on advisor FTE, expenditures on advisor FTE salaries, and on advisor FTE infrastructure. We have obtained data on a number of knowledge production methods; they are categorized into 11 subcategories, and 3 broad categories. We compute a weighted average knowledge index variable with the weights provided by UCCE county directors via an electronic survey. A limitation of the study is that we are able to capture only the contemporaneous impact of research inputs on the production of knowledge, due to data constraints. With availability of data, analysis of long run impact will enable policy makers to make informed decisions on investments in research inputs; this will enable sustained knowledge production and dissemination.

[12] The turning point of the production function is a point beyond which the slope changes from positive to negative; at this point the elasticity equals 0. This is obtained by solving the equation:
$\frac{\partial K/_K}{\partial I/_I} = \delta + 2\theta(lnI) = 0$. Plugging in the values of the coefficient estimates into the equation, we obtain $= e^{14.17/1.12}$, which gives us the value of expenditures on infrastructure per FTE at the turning point.

Coefficients indicate that all three inputs impact knowledge production positively. Expenditures on infrastructure per unit FTE as a research input has diminishing marginal returns to knowledge production. Marginal product of advisor FTE calculated at the mean value of the input and knowledge index equals 106.33[13]; this implies that one unit increase in county FTE leads to nearly 106 additional counts of knowledge production. Marginal products of expenditures on salaries per FTE and infrastructure per FTE are 0.003[14] and -0.0003[15], respectively. Marginal products values calculated at the mean emphasize the importance of advisor FTE as a research input. They also bring forward the issue of diminishing returns on investments in incentives and infrastructures.

There are some potential issues with the variable specifications, which deserve mention. The variable FTE includes UCCE county advisors. Incorporation of detailed data on knowledge produced and disseminated by UCCE specialists at the county level would provide a more complete picture of the knowledge production mechanism. Data on FTE experience and expertise could also refine our results and understanding of the input-output relationship. Research based agricultural knowledge is one of the most important inputs in the enhancement of agricultural productivity (Alston et al. 1998; 2008), and evidence suggests significant impacts of up to past 35 years of research-based knowledge on current productivity (Alston et al. 1998, 2008). Therefore better understanding of relevant research inputs, environments in which substitution between inputs is viable, and long term impact of shifts in investments in research inputs have a great deal of importance for policy purposes. This paper poses and provides answers to some of these questions and indicates possible directions for future study on this issue.

[13] This value equals ((1.1)·(358.63)/3.71).
[14] This equals ((0.87)·(358.63)/121,501.9).
[15] This value is calculated from the following expression: ((359.63/444,873.1)·(14.2 + 2*(-0.56) ·(ln(444,873.1)))

References

Joutz, F.L. and Abdih, M.Y., 2005. *Relating the knowledge production function to total factor productivity: an endogenous growth puzzle* (No. 5-74). International Monetary Fund.

Alston, J.M., Craig, B.J. and Pardey, P.G., 1998. *Dynamics in the Creation and Depreciation of Knowledge, and the Returns to Research* (No. 35). International Food Policy Research Institute (IFPRI).

Alston, J.M., Pardey, P.G. and Ruttan, V.W., 2008, September. Research lags revisited: concepts and evidence from US agriculture. In *Economic History Association meeting, New Haven CT* (pp. 12-14).

Birkhaeuser, D., Evenson, R.E. and Feder, G., 1991. The economic impact of agricultural extension: A review. *Economic development and cultural change*, *39*(3), pp.607-650.

Buesa, M., Heijs, J. and Baumert, T., 2010. The determinants of regional innovation in Europe: A combined factorial and regression knowledge production function approach. *Research Policy*,*39*(6), pp.722-735.

Cameron, A.C. and Trivedi, P.K., 2005. *Microeconometrics: methods and applications*. Cambridge university press.

Czarnitzki, D., Kraft, K. and Thorwarth, S., 2009. The knowledge production of 'R' and 'D'. *Economics Letters*, *105*(1), pp.141-143.

Dinar, A., 1991. Measuring knowledge production of an agricultural research system. *Technological Forecasting and Social Change*, *40*(3), pp.249-259.

Edquist, C., 2004. Reflections on the systems of innovation approach. *Science and Public Policy*, *31*(6), pp.485-489.

Evenson, R.E., 2001. Economic impacts of agricultural research and extension. *Handbook of agricultural economics*, *1*, pp.573-628.

Fritsch, M., 2002. Measuring the quality of regional innovation systems: a knowledge production function approach. *International Regional Science Review*, *25*(1), pp.86-101.

Griliches, Z., 1979. Issues in assessing the contribution of research and development to productivity growth. *The bell journal of economics*, pp.92-116.

Jin, Y. and Huffman, W.E., 2016. Measuring public agricultural research and extension and estimating their impacts on agricultural productivity: new insights from US evidence. *Agricultural Economics*,*47*(1), pp.15-31.

Jaffe, A.B., 1989. Characterizing the "technological position" of firms, with application to quantifying technological opportunity and research spillovers. *Research Policy*, *18*(2), pp.87-97.

Link, A.N., 1982. An analysis of the composition of R&D spending. *Southern Economic Journal*, pp.342-349.

Pardey, P.G., 1989. The agricultural knowledge production function: An empirical look. *The Review of Economics and Statistics*, pp.453-461.

Pavitt, K., 1985. Patent statistics as indicators of innovative activities: possibilities and problems. *Scientometrics*, *7*(1-2), pp.77-99.

Ponds, R., Van Oort, F. and Frenken, K., 2010. Innovation, spillovers and university–industry collaboration: an extended knowledge production function approach. *Journal of Economic Geography*, *10*(2), pp.231-255.

Sands, R.D., Jones, C.A. and Marshall, E., 2014. Global drivers of agricultural demand and supply.*Economic Research Report*, *174*.

Wooldridge, J.M., 2010. *Econometric analysis of cross section and panel data*. MIT press.

Appendix Table A1. Survey for County Directors.

Major types	**Direct Contact with Clients**				**Indirect Contact with Clients**					**Own Research Projects and Peer-Reviewed Journal Publications**					Total
Group Weight (%)															100
	Group Interactions (e.g. classes, workshops, demos)	Individual consultations (e.g., field visits, emails, phone calls with individual growers)	Other (e.g., presenting meetings, conference call, poster presentation)	TOTAL	Newsletters	Websites	Television and Radio	Other (e.g., booklets, hand-outs at meetings)	TOTAL	Peer reviewed journal publications	Basic Research Projects	Applied research projects	Other (management of student projects, development of programs)	TOTAL	
Within group weights (%)				100					100					100	

Appendix Table A2. Regression results for models using each of the 3 broad categories - direct, indirect contact, and publications and research projects as dependent variables. In columns (1) and (2), dependent variable is log of knowledge produced from all direct methods of contact, columns (3) and (4), dependent variable is log of knowledge produced from all indirect methods of contact with growers, and columns (5) and (6), dependent variable is log of knowledge produced from all peer-reviewed journal publications and research projects.

VARIABLES	(1) ln (Direct method)	(2) ln (Direct method)	(3) ln (Indirect method)	(4) ln (Indirect method)	(5) ln (Publications and research projects)	(6) ln (Publications and research projects)
ln(FTE)	0.92*	0.81	0.55	0.26	0.08	0.28
	(0.54)	(0.53)	(0.98)	(0.91)	(0.46)	(0.45)
ln(Salary/FTE)	0.89***	0.88***	0.58	0.47	0.52***	0.64***
	(0.25)	(0.25)	(0.47)	(0.46)	(0.17)	(0.15)
ln(Infrastructure/FTE)	17.77***	17.68***	7.81	7.36	2.09	3.59
	(6.19)	(6.43)	(12.58)	(11.62)	(5.37)	(5.58)
ln(Infrastructure/FTE) squared	-0.70***	-0.70***	-0.32	-0.30	-0.10	-0.16
	(0.25)	(0.26)	(0.51)	(0.47)	(0.22)	(0.22)
Constant	-116.3***	31.88	-49.17	398.4**	-13.86	251.1***
	(39.62)	(78.24)	(80.57)	(162.6)	(33.55)	(63.48)
Observations	290	290	271	271	285	285
R-squared	0.63	0.63	0.54	0.54	0.64	0.62
AIC	901.01	895.06	1256.93	1250.71	678.91	683.35
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO
Time Trend	NO	YES	NO	YES	NO	YES

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

Appendix Table A3. Regression results using the 3 subcategories under direct contact method of knowledge production, as dependent variables. In columns (1) and (2), dependent variable is log of knowledge produced from group interactions, columns (3) and (4), dependent variable is log of knowledge produced from individual consultations, and columns (5) and (6), dependent variable is log of knowledge produced from all other types of direct contact methods, categorized by UCCE.

VARIABLES	(1) ln(Group interaction)	(2) ln(Group interaction)	(3) ln(Individual consultation)	(4) ln(Individual consultation)	(5) ln(Other direct methods)	(6) ln(Other direct methods)
ln(FTE)	0.37	0.44	1.62*	1.06	0.32	0.26
	(0.62)	(0.58)	(0.82)	(0.77)	(0.56)	(0.51)
ln(Salary/FTE)	0.48	0.51	0.96**	0.76*	0.18	0.18
	(0.31)	(0.31)	(0.40)	(0.39)	(0.19)	(0.18)
ln(Infrastructure/FTE)	13.41**	12.97**	21.42***	19.72**	0.06	0.73
	(5.79)	(5.58)	(8.09)	(8.77)	(6.42)	(6.75)
ln(Infrastructure/FTE) squared	-0.54**	-0.52**	-0.84**	-0.78**	0.004	-0.02
	(0.23)	(0.23)	(0.33)	(0.35)	(0.25)	(0.27)
Constant	-83.10**	73.26	-146.3***	5.53	0.39	165.7***
	(37.78)	(85.62)	(51.93)	(147.8)	(40.52)	(63.26)
Observations	286	286	187	187	278	278
R-squared	0.63	0.63	0.58	0.55	0.59	0.57
AIC	892.90	886.59	689.04	689.80	804.33	805.11
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO
Time Trend	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses

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

Odd numbered columns (1, 3, 5) report regression results for models with county and year control dummy variables, and even numbered columns (2, 4, 6) for models with county control dummy variables and time trend.

Appendix Table A4. Regression results using the 4 subcategories under indirect contact method of knowledge production, as dependent variables. In columns (1) and (2), dependent variable is log of knowledge produced from newsletters, columns (3) and (4), dependent variable is log of knowledge produced from websites, columns (5) and (6), dependent variable is log of knowledge produced from TV and radio, and columns (7) and (8) dependent variable is log of knowledge produced from all other indirect methods of contact with growers, etc., as categorized by UCCE.

VARIABLES	(1) ln(Newsletters)	(2) ln(Newsletters)	(3) ln(Websites)	(4) ln(Websites)	(5) ln(TV & Radio)	(6) ln(TV & Radio)	(7) ln(Other indirect methods)	(8) ln(Other indirect methods)
ln(FTE)	0.59	0.16	0.67	0.37	-0.72	-0.06	-0.14	-0.58
	(1.34)	(1.27)	(0.63)	(0.56)	(3.23)	(2.64)	(0.75)	(0.74)
ln(Salary/FTE)	0.93	0.62	-0.20	-0.21	0.57	-0.16	0.39	0.33
	(0.74)	(0.72)	(0.23)	(0.20)	(1.23)	(1.11)	(0.25)	(0.24)
ln(Infrastructure/FTE)	50.86**	48.76**	-1.43	-2.36	40.90	38.98	-5.35	-4.91
	(20.92)	(19.58)	(5.32)	(4.88)	(80.66)	(73.70)	(8.01)	(7.44)
ln(Infrastructure/FTE) squared	-1.99**	-1.91**	0.07	0.10	-1.53	-1.43	0.20	0.18
	(0.83)	(0.78)	(0.22)	(0.20)	(3.14)	(2.87)	(0.32)	(0.30)
Constant	-329.7**	81.38	10.05	39.97	-277.9	-237.0	32.91	190.3
	(134.1)	(237.1)	(33.86)	(81.53)	(511.7)	(508.8)	(50.31)	(131.8)
Observations	236	236	189	189	84	84	207	207
R-squared	0.50	0.49	0.51	0.49	0.45	0.39	0.42	0.41
AIC	1156.16	1153.55	494.28	490.09	367.06	367.77	770.75	765.4
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO
Time Trend	NO	YES	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Odd numbered columns (1, 3, 5, 7) report regression results for models with county and year control dummy variables, and even numbered columns (2, 4, 6, 8) for models with county control dummy variables and time trend.

Appendix Table A5. Regression results using the 4 subcategories under publications and research projects method, as dependent variables. In columns (1) and (2), dependent variable is log of knowledge produced from peer-reviewed journal publications, columns (3) and (4), dependent variable is log of knowledge produced from basic research projects, columns (5) and (6), dependent variable is log of knowledge produced from applied research projects, and columns (7) and (8), dependent variable is log of knowledge produced from all other types of research projects and creative methods used to produce educational materials, as categorized by UCCE.

VARIABLES	(1) ln(Publications)	(2) ln(Publications)	(3) ln(Basic research)	(4) ln(Basic research)	(5) ln(Applied research)	(6) ln(Applied research)	(7) ln(Oher research projects)	(8) ln(Oher research projects)
ln(FTE)	1.38**	1.87***	0.50	-0.35	0.51	0.40	-1.66*	-1.56
	(0.58)	(0.61)	(1.29)	(1.09)	(0.35)	(0.37)	(0.98)	(0.10)
ln(Salary/FTE)	0.75***	1.252***	0.23	0.06	0.17	0.12	-0.078	0.05
	(0.27)	(0.29)	(0.37)	(0.41)	(0.15)	(0.15)	(0.33)	(0.32)
ln(Infrastructure/FTE)	8.93	13.02	-27.33	-19.39	-2.56	-2.74	6.56	7.22
	(7.55)	(9.08)	(19.40)	(15.19)	(4.07)	(4.06)	(6.20)	(6.11)
ln(Infrastructure/FTE) squared	-0.34	-0.50	1.08	0.75	0.11	0.11	-0.30	-0.33
	(0.30)	(0.36)	(0.77)	(0.59)	(0.16)	(0.16)	(0.26)	(0.25)
Constant	-66.54	115.3	169.7	246.6**	14.16	182.4***	-30.62	48.79
	(47.62)	(89.94)	(121.0)	(121.0)	(25.88)	(53.91)	(39.01)	(89.54)
Observations	238	238	82	82	260	260	183	183
R-squared	0.65	0.57	0.56	0.50	0.59	0.58	0.45	0.44
AIC	609.10	646.92	149.07	149.27	526.30	519.62	580.21	573.52
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO
Time Trend	NO	YES	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Odd numbered columns (1, 3, 5, 7) report regression results for models with county and year control dummy variables, and even numbered columns (2, 4, 6, 8) for models with county control dummy variables and time trend.

Appendix Table A6. Summary statistics for the 3 broad categories of knowledge production.

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
All direct methods	329	291.23	616.18	0	5419
All indirect methods	329	4406.72	20892.68	0	262205
All publications research methods	329	31.16	108.12	0	1890