Title
An empirical knowledge production function of agricultural research and extension: The case of the University of California Cooperative Extension

Journal
Technological Forecasting and Social Change, 134(C)

ISSN
0040-1625

Authors
Chatterjee, Diti
Dinar, Ariel
González-Rivera, Gloria

Publication Date
2018-09-01

DOI
10.1016/j.techfore.2018.06.037

Peer reviewed

Technological Forecasting & Social Change 134 (2018) 290–297

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

An empirical knowledge production function of agricultural research and extension: The case of the University of California Cooperative Extension

Diti Chatterjee[a], Ariel Dinar[b,*], Gloria González-Rivera[c]

[a] Department of Environmental Sciences, University of California, Riverside, United States of America
[b] School of Public Policy, University of California, Riverside, United States of America
[c] Department of Economics, University of California, Riverside, United States of America

ARTICLE INFO

JEL classifications:
C23
Q1
Q10
Q16

Keywords:
Knowledge production function
Cooperative extension
Agricultural R&D
University of California Cooperative Extension

ABSTRACT

Our study examines empirically the impact of agricultural research inputs on the creation and dissemination of knowledge by the University of California Cooperative Extension (UCCE). We formulate a conceptual framework to understand the relationship between the agricultural research inputs employed by UCCE and the knowledge shared. We develop an index of knowledge based on a weighted average of the various modes through which knowledge is produced by UCCE's agricultural research for all counties in the state of California during 2007–2013. Empirical results indicate significant positive impacts of research inputs on the production of knowledge. We find research input, such as number of research positions measured as full-time equivalent (FTE), level of salary per researcher (including seniority and status), and investment in research infrastructure per FTE, positive and significant. Our models suggest diminishing marginal knowledge returns to research infrastructure, and a linear knowledge production function with respect to the number of FTE and the salary per FTE in the UCCE system.

1. Introduction

Technological innovation has been identified as one of the important engines for economic development and growth (Griliches, 1979). It is driven through producing knowledge by firms and individuals, which allows them to stay competitive in the market (Buesa et al., 2010). Since the seminal paper by Griliches (1979), the concept of the knowledge production function has been further developed in theory (Czarnitzki et al., 2009) and applied at national (Perret, 2016), regional (Fritsch, 2002; hUallachain and Leslie, 2007; Charlot et al., 2014), sectoral (Gurmu et al., 2010), levels, and even using a meta-analysis of 15 individual studies (Neves and Sequeira, 2018).

Agriculture is one of the sectors in which innovation has become extremely important due to scarcity of natural resources, such as land and water, and increased demand for food driven by population growth. According to Food and Agricultural Organization (FAO) of the United Nations estimates,[1] global population is expected to grow by more than a third, or 2.3 billion people, between 2009 and 2050. Agricultural productivity would have to increase by about 70% 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 among the suggested prescriptions to ensure sustainable agricultural production. Sands et al. (2014) also predicted 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 guarantee continuous research and development in agriculture to sustain the current rate of productivity growth, and to increase it to counter both population growth and natural resource scarcity in the future. Such objectives can be met by proper investment in agricultural R&D and its dissemination to the agricultural producers. A first step is the identification of the process of converting research and dissemination inputs into knowledge used for improvement of food production.

Much of the literature reviewed in Section 2 below focuses on knowledge production functions in industrial firms and sectors. Fewer works apply the concept of knowledge production function to agricultural research (e.g., Alston et al., 1998; Dinar, 1991; Griliches, 1979; Pardey, 1989), and we are not aware of estimation of such function for agricultural extension. Agricultural extension is a public based research and dissemination of knowledge to farmers by universities and/or

* Corresponding author.
E-mail address: adinar@ucr.edu (A. Dinar).

[1] http://www.fao.org/fileadmin/templates/wsfs/docs/Issues_papers/HLEF2050_Global_Agriculture.pdf.

https://doi.org/10.1016/j.techfore.2018.06.037
Received 7 November 2017; Received in revised form 18 June 2018; Accepted 20 June 2018
Available online 28 June 2018

government agencies. In this paper, we apply the concept of knowledge production function to an agricultural extension system by focusing on research-based agricultural knowledge generated by the University of California Cooperative Extension (UCCE). This publicly-funded research and extension system has offices across counties within the state of 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. This paper contributes to the literature in several ways that set it apart from similar endeavors. To our knowledge, this paper is the first to develop a knowledge production function for an agricultural extension system that creates and disseminates knowledge, which is in itself an innovation. Second, it develops a weighted average value of knowledge, including a number of different components of knowledge produced. Third, the paper uses academic publications (as in Pardey, 1989, for an agricultural research system) to measure knowledge produced by extension, as opposed to patents used in measuring knowledge in private sector. Finally, it distinguishes knowledge production across California counties and over time, suggesting relative advantages in knowledge creation by counties with potential implications for public budget allocation.

The remainder of the paper is organized as follows: Section 2 reviews previous works and places our paper within that literature. Section 3 develops the econometric methodology, departing from the previous published work on agricultural knowledge that is reviewed in Section 2. Section 4 describes the data and variable creation. Section 4 reports the empirical results, and Section 5 presents the conclusion and policy implications.

2. Review of previous work

The knowledge production function has various applications at societal and sectoral levels. A recent published theoretical framework addressing the role of knowledge in society's growth was developed by Dolgonosov (2016). Distinguishing between technological knowledge and general total knowledge, the author demonstrated that knowledge is essential to allow sustainable population growth within the carrying capacity of the planet. The role of knowledge production is essential, especially with the increasing population and environmental load. This framework suggests that society could introduce policies to improve the efficiency of knowledge production in various sectors.

The literature distinguishes also between knowledge of various qualities. Cammarano et al. (2017) introduced the notion of quality of innovation output, using patent data from bio-pharmaceutical and equipment-producing companies. The analysis suggests a more productive knowledge process in which innovative firms use knowledge and information produced by external sources. Working on a related industry, Lauto and Valentin (2016) estimated a knowledge production function for what was coined the new science development model for clinical medicine, in which research can be conducted in a transnational effort, or locally. This is a very interesting distinction that may indicate the efficiency of transnational simultaneous research benefitting from a variety of conditions and its superiority to knowledge spillover of research conducted separately. However, the authors find that by its nature, transnational research may have lower efficiency and impact because it includes diverse aspects in quantitative comparisons. Some surprising findings are offered by Roper and Hewitt-Dundas (2015), who estimates the interaction between knowledge stocks and flows and their impact on the firm's innovation. They found (1) that negative rather than positive (although weak) effects between knowledge stocks and innovation (patents), and (2) knowledge flows dominate the effects of knowledge stocks on the innovation of the firm.

Several works address the issue of networking and proximity among the knowledge creation centers (Marrocu et al., 2013), and the effects of collaboration within and between regions on knowledge productivity (De Noni et al., 2017). Both works were applied to Europe. Ramani et al. (2008) develop a model of knowledge production function that can be estimated at both the firm and the sector level and apply it to the bio-food industry. The production function in this work allows to distinguish between the absorptive capacity to exploit inter- and intra-sectoral spillovers. Marrocu et al. (2013) found that technological proximity outperforms the geographic proximity, suggesting that networking has a limited role in enhancing knowledge creation. The most relevant finding of De Noni et al. (2017) to our work is that the impact on knowledge productivity is stronger in the case of collaboration between regions with diversified knowledge base. From a different perspective, Verspagen and De Loo (1999) addressed the spillover effect of knowledge, both across sectors and over time using a knowledge flow matrix. The methodology is very relevant for knowledge production investments, but it is heavily dependent on data that might not be readily available everywhere. Two examples of recent studies that address spillover effects in knowledge production are Wang et al. (2017) and Neves and Sequeira (2018). Wang et al. (2017) estimated the spillover effects in the semiconductor industry to find that the strength of the networking ties between companies explain the level of spillover effect in the knowledge production process. Spillover effects are expected to be stronger in weaker network ties. Neves and Sequeira (2018) conducted a meta-analysis of data from 15 published works to find expected, but reassuring results. They quantify level of spillover effects and discover that the spillover effect will be larger when they include in the estimation of the knowledge production foreign inputs, and it will be lower when only rich economics are included in the estimation.

Finally, universities are considered a hub for knowledge production, based on research conducted in addition to their role as educational institutions. Gurmu et al. (2010) used patents issued to universities during 1985–1999 as a measure of knowledge. They explained variation in knowledge by field of knowledge, R&D expenditures (over 4–8 previous years with a depreciation rate of knowledge of 15%), as well as detailed human capital variables, and several control variables. Their results indicated marginal contribution of each research variable to the production of knowledge.

While the literature review is by no means inclusive, it represents the many efforts that have been made in the literature for understanding the determinants of knowledge production. We will rely on these works while developing our analytical framework.

3. Analytical framework

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) estimated 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) reported positive impacts of both R&D and 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 as well as the 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 because measurement of knowledge produced from investments in R&D is conceptually and computationally complicated.

Griliches (1979) discussed the issues of measurement of knowledge production between public and private sector investments in R&D. He claimed 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 is paid for its use by others. Pavitt (1985) mentioned that patents are good proxy measures of innovative activities. Other studies (Buesa et al., 2010; Czarnitzki et al., 2009; Fritsch, 2002 and Ponds et al., 2010) have used patents as proxies for knowledge production. Data on patents are well documented in the United States and in 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 (1989) and Dinar (1991) used publications (the dependent variable) as a proxy for knowledge production. Publications are more prevalent in public research agencies, where research results are typically published in journals. Dinar (1991) used peer-reviewed journal publications in different fields as the dependent variable for his study of the agricultural research system in Israel. According to Pardey (1989), publications have been chosen over patented and non-patented output like mechanical innovation processes or new biological material, books, State Agricultural Experiment Station bulletins, and newsletters. Publications capture the knowledge output of a station completely because they establish intellectual property rights of the researchers over their work, which in turn affect their salary scale, promotion rate, and tenure status. Link (1982) analyzed the determinants of inter-farm differences on the composition of R&D spending, namely basic and applied R&D. He regressed these R&D components on profits, diversification, ownership structure, and subsidies. Jaffe (1989) found a 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 in the United States. The literature on the topic leads us to two main observations: (i) a dearth of papers that deal with the analysis of the knowledge production function and the study of the impact of production inputs on knowledge produced; and (ii) the choice of variables representing knowledge produced through investments in R&D only provides a partial picture of the true process. There is little attempt to compute a comprehensive knowledge production variable that 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 the needs of the clients at the county level. 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.

3.1. The model

The basic structure of the knowledge production function is similar to a standard production function in which 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. We keep the knowledge production function simple, accounting for the main extension-research inputs. We adopt the general specification of Fritsch (2002) that includes R&D expenditures and the number of research-related employees as inputs (plus fixed effects of various industries considered). We introduce fixed effects of the various counties of the state of California in the empirical function (2).

Therefore, the general form of the model is:

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

where $i = 1, 2\ldots, N$ county offices, $t = t_1, t_2, \ldots, t_n$. K is knowledge produced through expenditures made by UCCE. FTE is the full-time equivalent employment advisor positions. S is expenditures on salaries per-unit FTE. I represents the “non-salary related” expenditures on infrastructure, including benefits, travel expenses, and county extension programs.

The explicit econometric model, based on (1) that we estimate is presented in Eq. (2):

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

where ε_{it} is the error term, i is an index for all county offices and t is time, t = 2007–2013. K_{it}, FTE_{it}, S_{it}, I_{it}, are defined the same way as for Eq. (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 may diminish. It makes little sense to keep building laboratories and offices if there are no researchers or staff to fill them. We follow Roper and Hewitt-Dundas (2015:1334), who introduced the plant size as a quadratic Schumpeterian resource indicator, which has also been shown by Jordan and O'Leary (2007) to have an inverted-U shaped relationship with knowledge production. A similar specification by Charlot et al. (2014) lumps all R&D costs in a quadratic relationship due to economies and diseconomies of scale. The quadratic specification of infrastructure expenses means that over-investment in research infrastructure (non-salary expenditures) may turn to be counter-productive and to result in diminishing marginal productivity of knowledge production. To test this hypothesis, the square term for log of infrastructure expenses was included in our model. 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.

We use a log-log formulation for the knowledge production function, which is standard in the literature (Czarnitzki et al., 2009; hUallachain and Leslie, 2007; Perret, 2016) and is based on the assumption of a Cobb-Douglas-type production function with no restriction on returns to scale. Econometrically, this functional form is informative about input elasticities.

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

$$\frac{dK/dFTE}{K/FTE} = \beta \tag{3}$$

$$\frac{dK/dS}{K/S} = \gamma \tag{4}$$

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

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

We also estimate Eq. (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 (Wooldridge, 2010), 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.

4. Data

The University of California Cooperative Extension was established a century ago with the purpose of educating the citizens about agriculture, home economics, mechanical arts and other practical professions.[2] Through the course of almost a century since the Smith-Lever Act of 1914, the UC Cooperative Extension has grown into an elaborate system that has branched out from handling mainly farm-related issues to many other aspects concerning the farm, as well as the overall society. Extension advisors communicate practical research-based knowledge to agricultural producers, small business owners, youth, and consumers, who then adopt and adapt it to improve productivity and income. Today the UCCE works in six major areas,[3] including *Agriculture*, *4-H Youth Development*, *Natural Resources*, *Leadership Development*, *Family and Consumer Sciences*, and *Community and Economic Development*. This paper focuses on UCCE activities in agriculture.

The University of California Division of Agriculture and Natural Resources (UC ANR) headquartered in Oakland, California, is the source of data for the analysis in this paper. We collected annual budget data from the database for all UCCE county offices for the period of 2007 to 2013.[4] Our data set includes complete data for seven years for 47 county offices, which serve the 58 counties in California. There are six groups of two counties each, which are served by a single county office. And there is one office that serves four counties.

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 hereafter.[5] Henceforth, we will refer to the UCCE budget as expenditures, to avoid ambiguity. The expenditures made by UCCE are shown in panel (d) of Fig. 1. There is evidence of impact of the 2009–2010 recession on investments in 2010, which went 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 recorded some of the largest 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 were San Diego, Tulare, Kern, Plumas-Sierra, San Francisco, and San Mateo.

Data on salaries of advisors employed in each county office was collected from the UCCE database as well. Expenditures on infrastructure are the amount remaining in 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 was obtained for advisors employed by each county office. We observed an overall fall in both advisor FTE and advisor salaries, as represented in panel (a), Fig. 1. After 2010, both

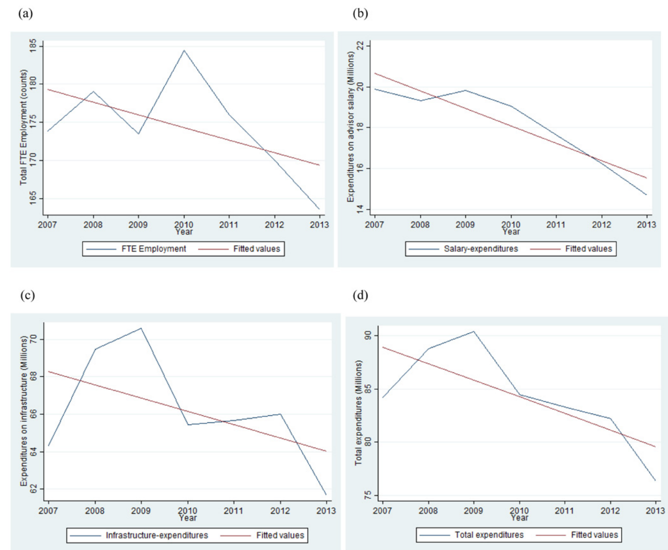

Fig. 1. Panel (a): Annual UCCE advisor FTE (counts); panel (b): Annual expenditures for UCCE advisor salaries (constant 2013 million USD); panel (c): Annual expenditures for UCCE infrastructures and programs (constant 2013 million USD); panel (d): Annual total expenditures of UCCE (constant 2013 million USD).

FTE and expenditures on salaries showed consistent decline. We observe (panel (c), Fig. 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 is created using data on a number of component variables. UC ANR 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 UCCE is publicly available 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 UC ANR, television, radio programs or public service announcements, social marketing methods, 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 educational purposes. We also include publications in peer-reviewed journals in this category. The above data on knowledge was recorded as counts. We were unable to categorize input variables into issues related to agriculture only, so to avoid overestimation issues, we include knowledge produced for all programs undertaken by UCCE for the period of the study.

Using the data on all knowledge categories, we generated an index

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

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

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

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

of knowledge as a weighted average of all the categories.[6] We assigned 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 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 so the sum would add up to 100%. Within each broad category, respondents indicated percentage weights for each subcategory so the sum of the weights also equaled 100%. We obtained 10 replies from county directors after two rounds of surveys and created weights from the survey results. The completed surveys indicated that the most important effect on agricultural productivity is direct contact with farmers (50%), followed by indirect contact with farmers (27%), and finally research and publications (23%).

From the data collected on knowledge production variables, we identified seven 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 potential clientele. Direct contact methods are costlier than indirect methods and have a more limited reach. Research projects, peer-reviewed publications, and the knowledge produced through them are also available to 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 with farmers by specialists and county advisors.

Over the period 2007–2013, we observe that all knowledge production declined as is illustrated in Fig. 2. Total knowledge produced in 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%, from 15,059 in 2007 to 21,479 in 2011, but thereafter it continued falling until it reached a total count of 8282 in 2013, which is a 61% decrease compared to 2011. Knowledge produced through different methods of indirect contact with growers starts at 259,065 in 2007, and peaks at 405,386 in 2009, before falling down to nearly 43,000 counts per year in 2010. In 2013, the recorded number is 100,919, which is equivalent to a 61% reduction from the original levels in 2007. Research projects and peer-reviewed journal publications went down from 3349 in 2007 to 506 in 2013, which is a percentage decline of nearly 85% of the 2007 value.

Among all the counties, San Diego recorded the highest average (over time) count of knowledge production from direct methods, at 1714[7] (maximum 2817, minimum 470), and Madera the lowest, at 3 (maximum 17, minimum 0). San Joaquin had 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 had 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).

We also observe 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.

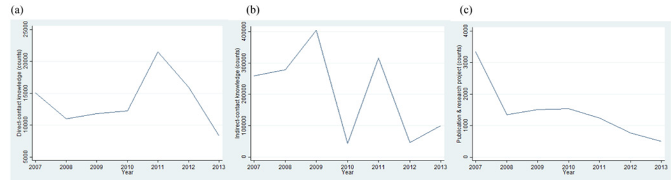

Fig. 2. Panel (a): Counts of direct methods of knowledge production; panel (b): Counts of indirect methods of knowledge production; panel (c): Counts of research and creative activity methods of knowledge production.

5. Results and discussion

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. At the county level, San Joaquin, one of the most important agricultural producers, presents the highest mean knowledge index over 2007–2013, while Madera had the lowest. Mean advisor FTE number in San Joaquin was 353% higher than that in Madera; with 36% lower expenditures on salaries per unit FTE, and a 1% lower expenditures on infrastructure per FTE, compared to Madera county.

The knowledge index, the weighted average of counts of the component variables, had been declining for the period of our study, as seen in Fig. 3. The cross-sectional average value of log (knowledge index) went down from about 3.9 to about 2.75 over the period of 2007–2013, which reflected a 68% decline in the knowledge index. With these observations, it is important to know how our inputs impacted the average knowledge produced, and how these declining trends in inputs may have impacted knowledge production. Similar trends in knowledge production in agriculture are reported also by Alston et al. (2013) and by Ball et al. (2013) for the USA as a whole.

Table 2 reports the regression results of Eq. (2), including two different models. Column (1) reports the results for the case in which we include county and year level dummy variables to control for any factors that remain fixed across counties or years, possibly impacting the dependent variable. This is a noticeable contribution to the literature because recent works on agricultural knowledge production function estimates have been focused on state level or national level. However, decisions on allocation of funding for knowledge production in extension activities have been made at the county level. The second version of the model (Column (2)) includes a time trend instead of time-fixed effects. The specification with time trends allows to treat time effects on knowledge production as a continuous rather than fixed effect variable, which potentially can be more useful for policy makers. In the case of our analysis, these two models produced very similar results as is discussed below.

We obtained statistically significant coefficients for all the input variables in both versions of our model reported in columns Model (1) and Model (2) of Table 2. A percentage rise in FTE impacted knowledge production positively by nearly 1.1%. A 1% rise in expenditures on salaries per unit FTE increased knowledge production by 0.86%. The coefficient estimate for the linear term of expenditures on infrastructures per unit FTE is positive and the coefficient estimate for the quadratic term is negative, supporting the theory of diminishing marginal returns to expenditures in infrastructure per FTE employee. In Model (2), we controlled for county-level fixed effects by introducing county dummy variables. Here, we de-trended the dependent variable as well as the independent variables by including a time trend variable in the model. We reported robust standard errors in the parentheses.

[6] 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, …0.47 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 'k' representing the subcategories.

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

Table 1
Summary statistics[1].

Variable	Observations	Mean	Std. dev.	Min	Max
FTE	329	3.71	2.49	0.2	12.1
Salary/FTE	329	121,501.9	149,510.7	2066.23	2656,400[2]
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 interaction	329	57.75	187.22	0	2374
Newsletters	329	4269.51	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	12,002
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.

[1] 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.

[2] 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%. The normalization of the salary expenditure by the FTE leads us to this number.

Fig. 3. Annual mean ln (knowledge index).

Coefficient estimates for both the models are comparable to each other. While it is difficult to compare our results in Table 2 for an agricultural research and extension system to results of work on industrial knowledge production function, still there are several similarities in terms of the relative importance and the sign of the coefficients of the estimated knowledge function to the work of Czarnitzki et al. (2009).

We computed the elasticities of production, based on results in Table 2, which are reported in Table 3 below.

The elasticity of production of knowledge with respect to FTE varied from 1.07 and 1.10, across the two models we estimated. The elasticity of knowledge production with respect to salary level varied between 0.86 and 0.87 across the two estimated models. The elasticity of knowledge production with respect to infrastructure expenditures varied between −0.39 and −0.31 across the two estimated models. The interpretation of these estimates is as follows: A 1% increase in FTE led to a 1.1% increase in average knowledge produced. Similarly, a 1% increase in expenditures on salaries per unit FTE would bring about a 0.87% increment in average knowledge produced by UCCE. The elasticity for expenditures on infrastructures per FTE for both models were calculated (due to the quadratic nature of infrastructure expenditure) at the sample mean of this variable (444,873.1), using Eq. (5), as reported

Table 2
Regression results with log weighted average of knowledge (knowledge index) as dependent variable.[1]

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

[1] We also estimate Eq. (2) using the same inputs of production but with a disaggregated dependent variable that accounts for each of the 3 broad knowledge categories and for each sub category. Several results are shown in Appendix Tables A2, A3 and A4. For more details see Chatterjee et al., 2016.

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

in Table 3. This value is negative, both in Model (1), and Model (2). Due to diminishing marginal returns, the 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 computed the value of expenditures on infrastructure per unit FTE that corresponds to the turning point of the production function from a positive to a negative slope; this value equals $312,320.[8] 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 observed that FTE is the most effective input in the knowledge production process, with an elasticity > 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) found 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 an incentive system to make the current advisor FTE more productive, which enhances productivity, as is indicated by our results. Expenditures on infrastructure have a positive impact on knowledge production before the threshold level is reached, beyond which the impact becomes negative. In this respect, our findings for the extension system in California suggest that the research and dissemination by agricultural extension is similar to that of a research-only system.

The quadratic behavior of the expenditures on infrastructure was found significant, with a negative sign for the quadratic term. This finding is similar to the results in Roper and Hewitt-Dundas (2015), Jordan and O'Leary (2007), and Charlot et al. (2014). Such results suggest an inverse U-shaped relationship between knowledge production and fixed infrastructure investment. The support in findings on the inverse U-shaped impact of research infrastructure on knowledge production we get from literature on non-agricultural research, is very helpful for validating the results in our analysis with focus on agricultural research and extension in California.

The coefficients indicate that all three inputs impacted knowledge production positively. We found that expenditures on infrastructure per-unit FTE as a research input has diminishing marginal effects on knowledge production. Marginal product of advisor FTE calculated at the mean value of the input and knowledge index equals 106.33[9]; this implied that one unit increase in county FTE led to nearly 106 additional counts of knowledge production. Marginal products of expenditures on salaries per FTE and infrastructure per FTE are 0.003[10] and −0.0003,[11] respectively. Marginal products values calculated at the mean emphasized the importance of advisor FTE as a research input. They also brought forward the issue of diminishing returns on investments in incentives and infrastructures.

We conducted several robustness checks by running regression for models using each of the three broad categories of knowledge production and dissemination instead of the calculated knowledge index. The three broad categories are: direct contacts, indirect contact, and publications and research projects as dependent variables. The results of the robustness checks are reported in Appendix Tables A2, A3, and A4. The results suggest similar range of coefficients for each of the variables, similar signs and significance levels (although this parameter was the one showing highest variation) across the various estimated models. Thus, these results suggest that the empirical knowledge function we use is robust.

Endogeneity, if exists, could be found in the sphere of budget allocation for extension work (research and dissemination) at the county level. It could be argued that level of budget allocation is a function of the agricultural performance of the county, and thus introducing endogeneity biases in our estimates. However, following interviews with county directors, decisions on budget allocations among the counties in California are made based on political negotiations between the county directors and the UCCE system. Furthermore, as suggested by Guttman (1978), Rose-Ackerman and Evenson (1985), Pardey (1989) and Pardey and Craig (1989), political rather than just economics efficiency criteria influence the allocation of public agricultural research and extension resources.

6. 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 in all California counties. Available data on R&D expenditures and knowledge products was used to construct a unique data set for seven years, spanning from 2007 to 2013. The data contained information on extension advisor FTE, expenditures on advisor FTE salaries, and on advisor FTE infrastructure. We obtained data on a number of knowledge production and dissemination methods. They are categorized into 11 subcategories, and three broad categories. We computed a weighted average knowledge index variable with the weights provided by UCCE county directors via an electronic survey.

The contribution of this work is the quantification of extension research input and in the fact that the trends and relative importance of research variables found in an extension research and dissemination system in California are similar to (1) previous results of the agricultural research system in the USA, and (2) previous results from several industrial research and development activities around the world. Both these similarities suggest that a research and dissemination agricultural extension behaves similarly to industrial research systems.

One limitation of the study is that we were able to capture only the contemporaneous impact of research inputs on the production and dissemination of knowledge, due to data constraints. With further availability of data, analysis of long-run impact will enable policymakers to make informed decisions on investments in research inputs. This will enable sustained knowledge production and dissemination.

Another limitation of the study is the lack of information on components of the research inputs, such as attributing research outcomes and extension impact to advisors, rather than distinguishing among advisors, based on seniority and experience. Such a distinction related to university research was performed in a study by Gurmu et al. (2010).

Some potential issues with the variable specifications deserve a 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 on current productivity from the past 35 years of research-based knowledge (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.

Another point to address is the international and national relevance

[8] 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.

[9] This value equals ((1.1)·(358.63)/3.71).

[10] This value equals ((0.87)·(358.63)/121,501.9).

[11] This value is calculated from the following expression: ((359.63/444,873.1)·(14.2 + 2*(−0.56)·(ln(444,873.1))).

of this work to the literature and to policy practitioners. California is a leader in agricultural production. California extension system is a leader in extension knowledge that feeds into the agricultural production in the state. Therefore, understanding the process of knowledge creation by agricultural extension in California is of interest to researchers and practitioners in other states and countries. The finding in this study suggests that data collection and analysis for public extension activities are essential for proper policy consideration of a public knowledge system, which faces budget pressure world-wide. While the coefficients estimated for the case of California represent California situation, the trends of the coefficients are general and relevant to other states and countries around the world. With the data challenges we faced in this study, our results indicate the importance of the policy-maker to be able to quantify the process of knowledge production in the agricultural extension systems. California ranks first among the top five national agricultural producers, according to the California Statistical Review 2014–15 (CDFA, 2015), with crop cash receipts amounting $53.5 billion (13% of the nation's total). Irrigated agriculture in California consumes on average about 85% of the available renewable water resources in the state (Hanak et al., 2011). Agricultural extension plays a major role in keeping agriculture sustainable and profitable (Jin and Huffman, 2016). Therefore, the need for a reliable system of data collection on agricultural extension activities and knowledge produced at the state and county levels would enhance the ability to identify the determinants of knowledge production by the extension system.

Finally, we observed, as Pardey (1989) and Alston et al. (2013) also did, that the public budget allocated to agricultural and extension has declined over time. The lesser funding allocated to UCCE over time is not because knowledge has decreased; in fact, we claim that it is the opposite, knowledge production has declined because there was less funding due to recession or/and budgetary constraints in the University of California system as a result of financial difficulties faced by the state of California during the years we analyze.

Acknowledgements

Partial funding for the research leading to this paper was provided by the Office of the Vice President in the University of California Division of Agriculture and Natural Resources (ANR), and from The Giannini Foundation for Agricultural Economics mini grant program.

References

Alston, J.M., Craig, B.J., 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., Ruttan, V.W., 2008, September. Research lags revisited: concepts and evidence from US agriculture. In: Economic History Association Meeting, pp. 12–14 (New Haven CT).
Alston, J.M., Pardey, P.G., Chan-King, Connie, 2013. What can be Done to Reinvigorate U.S. Agricultural Research? ARE Update. 16(6). University of California Giannini Foundation of Agricultural Economics, pp. 9–12 (June 2013).
Ball, E., Schimmelpfennig, D., Wang, S.L., 2013. Is U.S. agricultural productivity growth slowing? Appl. Econ. Perspect. Policy 35 (3), 435–450.
Birkhaeuser, D., Evenson, R.E., Feder, G., 1991. The economic impact of agricultural extension: a review. Econ. Dev. Cult. Chang. 39 (3), 607–650.
Buesa, M., Heijs, J., Baumert, T., 2010. The determinants of regional innovation in Europe: a combined factorial and regression knowledge production function approach. Res. Policy 39 (6), 722–735.
Cammarano, A., Michelino, F., Lamberti, E., Caputo, M., 2017. Accumulated stock of knowledge and current search practices: the impact on patent quality. Technol. Forecast. Soc. Chang. 120, 204–222.
CDFA, California Department of Food and Agriculture, 2015. California Agricultural Statistics Review 2014–2015. State of California, Sacramento.
Charlot, S., Crescenzi, R., Musolesi, A., 2014. Econometric modeling of the regional knowledge production function in Europe. J. Econ. Geogr. 1–35. (ISSN 1468-2702). https://doi.org/10.1093/jeg/lbu1035.
Chatterjee, D., Dinar, A., González-Rivera, G., 2016. A Knowledge Production Function of Agricultural Research and Extension: The Case of the University of California Cooperative Extension. UCR SPP Working Paper Series (September 2016, WP# 16-06). http://spp.ucr.edu/publications/knowledge-agricultural-research.pdf.
Czarnitzki, D., Kraft, K., Thorwarth, S., 2009. The knowledge production of 'R' and 'D'. Econ. Lett. 105 (1), 141–143.
De Noni, I., Ganzaroli, A., Orsi, L., 2017. The impact of intra- and inter-regional knowledge collaboration and technological variety on the knowledge productivity of European regions. Technol. Forecast. Soc. Chang. 117, 108–118.
Dinar, A., 1991. Measuring knowledge production of an agricultural research system. Technol. Forecast. Soc. Chang. 40 (3), 249–259.
Dolgonosov, B.M., 2016. Knowledge production and world population dynamics. Technol. Forecast. Soc. Chang. 103, 127–141.
Evenson, R.E., 2001. Economic impacts of agricultural research and extension. Handb. Agric. Econ. 1, 573–628.
Fritsch, M., 2002. Measuring the quality of regional innovation systems: a knowledge production function approach. Int. Reg. Sci. Rev. 25 (1), 86–101.
Griliches, Z., 1979. Issues in assessing the contribution of research and development to productivity growth. Bell J. Econ. 92–116.
Gurmu, S., Black, G.C., Stephan, P., 2010. The knowledge production function from university patenting. Econ. Inq. 48 (1), 192–213.
Guttman, J.M., 1978. Interest groups and the demand for agricultural research. J. Polit. Econ. 86, 467–484.
Hanak, E., Lund, J., Dinar, A., Gray, B., Howitt, R., Mount, J., Moyle, P., Thompson, B., 2011. Managing California's Water: From Conflict to Reconciliation. PPIC, San Francisco.
hUallachain, B.O., Leslie, T.F., 2007. Rethinking the regional knowledge production function. J. Econ. Geogr. 7, 737–752.
Jaffe, A.B., 1989. Characterizing the "technological position" of firms, with application to quantifying technological opportunity and research spillovers. Res. Policy 18 (2), 87–97.
Jin, Y., Huffman, W.E., 2016. Measuring public agricultural research and extension and estimating their impacts on agricultural productivity: new insights from US evidence. Agric. Econ. 47 (1), 15–31.
Jordan, D., O'Leary, E., 2007. Sources of innovation in Irish SMEs: evidence from two Irish regions. In: British–Irish Regional Science Association Annual Conference, Bangor.
Lauto, G., Valentin, F., 2016. The knowledge production model of the new sciences: the case of transnational medicine. Technol. Forecast. Soc. Chang. 111, 12–21.
Link, A.N., 1982. An analysis of the composition of R&D spending. South. Econ. J. 342–349.
Marrocu, E., Paci, R., Usai, S., 2013. Proximity, networking, and knowledge production in Europe: what lessons for innovation policy? Technol. Forecast. Soc. Chang. 80, 1484–1498.
Neves, C.P., Sequeira, T.N., 2018. Spillover in the production of knowledge: a meta-regression analysis. Res. Policy 47, 750–767.
Pardey, P.G., 1989. The agricultural knowledge production function: an empirical look. Rev. Econ. Stat. 71 (3), 453–461.
Pardey, P.G., Craig, B., 1989. Casual relationships between public sector agricultural research expenditures and output. Am. J. Agric. Econ. 71, 9–19.
Pavitt, K., 1985. Patent statistics as indicators of innovative activities: possibilities and problems. Scientometrics 7 (1–2), 77–99.
Perret, J., 2016. An alternative approach towards the knowledge production function on a regional level-application for USA and Russia. In: Schumpeter Discussion Papers, 2016–003 Schumpeter School of Business and Economics. University of Wuppertal.
Ponds, R., Van Oort, F., Frenken, K., 2010. Innovation, spillovers and university–industry collaboration: an extended knowledge production function approach. J. Econ. Geogr. 10 (2), 231–255.
Ramani, S.V., El-Aroui, M., Carrere, M., 2008. On estimating a knowledge production function at the firm and the sector level using patent statistics. Res. Policy 37, 1568–1578.
Roper, S., Hewitt-Dundas, N., 2015. Knowledge stocks, knowledge flows and innovation: evidence from matched patents and innovation panel data. Technol. Forecast. Soc. Chang. 44, 1327–1340.
Rose-Ackerman, S., Evenson, R.E., 1985. The political economy of agricultural research and extension: votes and reappointments. Am. J. Agric. Econ. 67, 1–14.
Sands, R.D., Jones, C.A., Marshall, E., 2014. Global drivers of agricultural demand and supply. Econ. Res. Rep. 174.
Verspagen, B., De Loo, I., 1999. Technology spillover between sectors and over time. Technol. Forecast. Soc. Chang. 60, 215–235.
Wang, C.-C., Sung, H.-Y., Chen, D.-Z., Huang, M.-H., 2017. Strong ties and week ties of the knowledge spillover network in the semi-conductor industry. Technol. Forecast. Soc. Chang. 118, 114–127.
Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data. MIT press.

Diti Chatterjee is an Economist with A2F Consulting in Bethesda, MD, USA.

Ariel Dinar is a Distinguished Professor of Environmental Economics and Policy at the School of Public Policy, University of California, Riverside, USA.

Gloria González-Rivera is a Professor of Econometrics at the Department of Economics, University of California, Riverside, USA.