THE PRODUCTION AND DISSEMINATION OF AGRICULTURAL KNOWLEDGE AT U.S. RESEARCH UNIVERSITIES: THE ROLE AND MISSION OF LAND-GRANT UNIVERSITIES

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Abstract
This paper analyzes food and agriculturally-related knowledge production and transfer for 114 top-tier U.S. research universities from 1993 to 2015, to understand the role of the Land-Grant universities in promoting commercial innovation and regional economic development in this sector. We utilize two empirical methods: (1) a panel analysis of the knowledge production function (KPF) for research productivity and (2) an analysis of variance (ANOVA) for the role of the Land-Grant universities in such knowledge production. Output of research publications exhibits decreasing returns to scale for all sub-fields, but cost advantages and mean research (gestation) lags vary by sub-field. The mean number of research publications by the Land-Grant universities is much higher than non Land-Grant universities, especially in the Central region of the U.S. These results demonstrate how specialization by Land-Grant universities in agricultural R&D contributes to commercial innovation within a diffuse yet regionalized industry. Moreover, the main context and results of this paper would suggest some important implications to the study of the system of food and agricultural R&D and commercial innovations in Korea.

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I. Introduction and Background

In the global knowledge economy, universities play a significant role in knowledge creation and transfer. Today, most research universities are engaged in industrial innovation and regional economic development, leading to positive social returns (Jaffe 1989; Mansfield 1991, 1995; Audretsch and Feldman 1996; Adams and Griliches 1998; Cowan, 2005). Following Cohen, Nelson, and Walsh (2002), university research is identified to be of at least moderate importance to R&D within a wide range of industries, including both high technology and more traditional. Moreover, studies have measured the contributions of academic research to industrial innovation and the introduction of new products and processes through different knowledge dissemination channels and different modes of impact (Mansfield 1991 and 1995; Henderson et al., 1998; Agrawal and Henderson, 2002).

In the United States in 2013, university research accounted for roughly 50 percent of total basic research, and universities make up the second largest performer of research and development (R&D) after industry, accounting for $64.7 billion of the total $456 billion, or 14 percent, of R&D performed (NSF 2016). By far the largest source of funding for university performed R&D was the U.S. federal government; while the share of university R&D expenditures funded by the business sector accounted for just $3.5 billion or 5.4 percent. In the agricultural and food industries in the U.S. total expenditures on R&D in 2013 was $16.3 billion. Of that total, public research institutions—including the system of the Land-Grant universities, together with the state agricultural experiment stations (SAES) and Cooperative Extension institutions—accounted for almost 30 percent of the total agricultural and food R&D expenditures, over twice the level compared to the economy as a whole (USDA ERS 2016; Clancy et al. 2016).

In the U.S., the Land-Grant universities have long focused on providing agricultural R&D and, in so doing, have served as a source of ideas for commercial innovation and regional economic development. Historically, the Land-Grant system was very closely associated with the development of the U.S. public higher education system driven by several landmark policy changes, including the Morrill Land-Grant Act of 1862 and 1890, the Hatch Act of 1887, and the Smith-Lever Act of 1914[1]. Following these landmark policies, the Land-Grant universities have generally come to embrace three interwoven missions in education, research, and outreach. The Morrill Land-Grant Acts of 1862 and 1890 provided funds, through the granting of land assets by the federal government, to each state of the United States, according to the act:

"for the endowment, support, and maintenance of at least one college where the leading object shall be, without excluding other scientific and classical studies, and including military tactics, to teach such branches of learning as are related to agriculture and the mechanic arts, … in order to promote the liberal and practical education of the industrial classes in the several pursuits and professions in life."

The Hatch Act of 1887 created and funded state agricultural experimental stations for each state, which were often established as the research division of the state's new Land-Grant college or university, to conduct R&D specific for that state's agricultural industry and rural economy. Finally, the Smith-Lever Act of 1914 created and funded the Cooperative Extension Service) as an integral part of the states' land-grant college or university, yet funded and managed cooperatively with the state government, to provide information and education regarding agriculture throughout the state's local communities.

Today, the public Land-Grant universities make up the largest share of the top-tier research universities in the U.S. In this analysis, we will see that, of the 114 universities classified by the Carnegie Classification of Institutions of Higher Education as "R1 research universities", 41 (or 36 percent) are Land-Grant universities. Altogether, 70 percent of these top-tier universities are public universities, yet the non Land-Grant public universities make up 34 percent of the total. Private universities make up just 30 percent of the total. Moreover, still today, the Land-Grant universities continue to maintain education, research, and outreach programs in areas related to agricultural sciences and engineering (a.k.a. the "mechanical arts"). And, in each of the states of the United States today, the Land-Grant university's production of new scientific knowledge and transfer of new technology to industry continue to be important factors spurring the creation of agricultural innovations, driving investment and engagement by the private sector, and providing opportunities for rural economic development.

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[1] More information: https://nifa.usda.gov/history

The production of such economically-useful knowledge can be measured in several different ways. This makes it possible to analyze the extent to which different types of knowledge dissemination channels are utilized by universities. These can include channels such as the public domain, university-industry collaboration, patent licensing, and venture creation (Lee and Graff 2017). Since universities and public research institutions are generally recognized as non profit organizations, most results of university research are released into the public domain, via publications and open access of research results, given that the role of university is largely to serve public purposes. Recently, however, the emergence of the "entrepreneurial" university characterized by the commercial utilization of university research results have induced new processes or modes of university R&D and dissemination activities, which are based on the intellectual property rights (IPRs)[2] and collaborative research projects conducted jointly with industry sponsors and partners, expanding the mission and role of the university[3] (Etzkowitz 2003).

Although both formal IP-mediated tech transfer activities and more informal industry collaboration and extension activities are used to disseminate knowledge outputs from the university, the public domain-oriented knowledge outputs—such as published journal articles, conference proceedings, book chapters and reviews, public lectures, and even degree awards—are still the major knowledge outputs of any university. In fact, the magnitude and size of knowledge outputs produced and disseminated via the public domain are significantly greater than the knowledge outputs produced and disseminated via the traditional industry collaboration and the formal IP-mediated tech transfer activities. Because of the nature of knowledge, the different types of knowledge outputs are closely intertwined and have complex complementary and substitute relationships depending upon the context (Agrawal and Henderson 2002; Payne and Siow 2003; Bonaccorsi et al. 2006; Thursby and Thursby 2011; Folz et al. 2007; Lee and Graff 2017). Thus, the public domain-oriented knowledge outputs should continue to be considered the primary output of the university and likely to affect the pro-

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[2] By the passage of the Bayh-Dole Act of 1980, the U.S. university inventors have been permitted to possess the ownership of their patented inventions, which made with federal funding. Moreover, due to the increase in university-industry collaborations, university inventors have possessed the co-ownership of private funded inventions, and become co-founders of new startup companies.

[3] The outreach mission of economic and social development, as well as the mission of teaching and research.

duction of the other types of knowledge outputs, even though the extent and direction of causality may not be fully resolved[4].

The geographic proximity between university and industry is also important for university R&D and dissemination activities (Jaffe 1989; Jaffe et al. 1993; Audretsch and Feldman 1996; Anselin et al. 2000; Adams 2002; Boschma 2005; Ponds 2010; Buenstorf and Schacht 2013). As demonstrated by the history of the Land-Grant university system in the U.S., the university's outreach mission (regional economic development) is intimately linked with the geographic distance, with more proximate industry likely to have a cost advantage in absorbing and using new knowledge from the university. Generally, shorter distances mean lower transaction costs. However, this rule of proximity is not applicable in every circumstance, and in fact it may vary systematically across the different types of knowledge dissemination. According to Jaffe (1989), geographic proximity is unimportant if the knowledge channel is based on publications, but geographic proximity is important if the channel is based on informal exchange. Moreover, due to the improvement of telecommunication and information technologies today, some of the underlying mechanism of knowledge spillovers between university and industry may not be as constrained by regional proximity today as it was in the past.

However, within the context of the formation of industry clusters, wherein sets of interrelated private sector firms and associated public institutions within particular fields of industry or technologies tend to aggregate in the same region, geographic proximity does appear to remain important. In agriculture, following Graff et al. (2014), innovation clusters in the food and agriculture-related industries can be shaped by the structure of the food and agricultural value chain within a state, which in turn is affected by the relationships between the region's industry and public research institutions.

The main purpose of this paper is to analyze the system of agriculturally-related knowledge production and transfer activities across the 114 top U.S. research universities, over more than two decades, from 1993 to 2015. This paper introduces and explores several empirical specifications of a more general model of the knowledge production function (KPF), utilizing a detailed dataset of uni-

[4] According to Agrawal and Henderson (2002), the patent volume does not predict the volume of publications and vice versa, but patent volume seems to be positively correlated with the paper citations. They also point out that finding the correlation between patenting and publication activities is difficult but it is an important and meaningful question.

versity knowledge inputs and outputs, including life science research expenditures and several different categories of food and agriculture-related research publications, respectively. The main research questions of this study concern the systematic relationship between research inputs and outputs by universities in agriculturally related fields of research: How does the productivity as well as the timing and lag structure of knowledge production vary across different ag-related research fields? How does output of agriculturally-related knowledge differ for the Land-Grant universities, which have historically specialized in these fields, and all other universities? To what extent do such differences seem to be related to the geographic location of Land-Grant universities and the regional profile of the agricultural and food industries? These questions have important implications for knowledge output, innovation and productivity growth, and regional economic development, particularly for those regions that are more dependent upon or specialized in agricultural and food production. Finally, we explore how these questions and the results of this analysis apply to food and agriculture-related research and innovation in South Korea.

The rest of this paper is organized into four sections. Section II describes a technique for estimating the knowledge production function involving panel count data within a polynomial distributed lag scheme using a novel research input-output data set. Section III shows the results for the empirical tests by the 114 top tier research universities in the United States from 1993 to 2015. Then from an analysis of variance (ANOVA), we look at the relationship between the geographic location of Land-Grant universities and the dissemination of new knowledge in different ag related research fields via research publications. Section IV discusses important implications for food and agriculturally-related research and innovation in Korea based on the results of this study. Section V summarizes the main conclusions and insights of this study.

II. Model Framework and Data

1. Empirical model framework

The knowledge production function (KPF) is based on the concept of the neo-classical production function, and it is useful for describing the unobservable, yet valuable, additions that research contributes to the stock of knowledge capital. However, the production of knowledge differs from that of normal economic goods in two major ways. First, the profit maximization problem is rarely applied to the knowledge production problem due to the lack of a stable, appropriated market price of research outputs. Second, the units or increments of actual or "underlying" economically valuable technological knowledge are often unobservable. According to Pardey (1989), empirical studies of knowledge production is limited in large part because of the difficulties of obtaining suitable indicators of research outputs. Nevertheless, the literature demonstrates that we can be confident that there exists a systematic input-output relationship between research inputs and new knowledge outputs as measured by a number of proxy variables. In this study, we estimate three different specifications of the knowledge production function (KPF) in which output is measured by the count of research publications: (1) a log-log model with an unrestricted PDL scheme, (2) a negative binomial MLE model with unrestricted PDL scheme, and a negative binomial MLE model with restricted PDL scheme.

The initial idea and functional form of the knowledge production was introduced by Griliches (1979) and Pakes and Griliches (1980 and 1984). Specific to agriculture, Parday (1989) adapted the knowledge production function (KPF) to 48 state Land-Grant universities and their state agricultural experimental stations (SAESs) over 13 years. In classical production theory, there are various functional forms for representing the relationship between inputs and outputs, such as log linear, quadratic, Cobb-Douglas, CES, transcendental, von Liebig, Mitscherlich-Baule, translog, etc. However, most previous empirical studies of knowledge production have utilized one of most common, the Cobb-Douglas production function, because of its amenability to econometric techniques but also because of its suitable representation of some of the inherent characteristics of knowledge production. Equation (1) represents the log-linear form of the Cobb-Douglas or the log-log KPF model[5] adapted from Griliches (1979) and from Pardey (1989):

(1) $\ln Y_{i,t} = \alpha + \sum_{j=0}^{k} \beta_j \ln R_{i,t-j} + \varepsilon_{i,t}$

where Y is the logarithm of the university knowledge outputs[6] and R is the logarithm of the $j=0,\ldots,k$ lagged time period of the research expenditures for research university i at time t. ε is an *independent and identically distributed* panel disturbance term[7].

Before developing the main model, we need to outline two major issues: (1) the count data dependent variable and (2) the lag scheme of the relationship between the input of past research expenditures and the output of research publications. First, most university research outputs are measured by count data[8], such as the number of publications per year, the number of degree awards per year, the number of patent applications and issued patents per year, etc. So, we attempt to use negative binomial maximum likelihood estimation (MLE) models as the countable dependant variable (see Hausman et al. 1984; Hall et al. 1986) and the log-likelihood function is equation (2) below:

(2) $\ln L(\boldsymbol{\beta} | Y_{i,t}, \boldsymbol{\theta}_{i,t}) = \sum_{i=0}^{N} \ln \left[\frac{\Gamma(Y_{i,t}+\gamma)}{Y_{i,t}!\Gamma(\gamma)} \left(\frac{\gamma}{\gamma+\boldsymbol{\theta}_{i,t}} \right)^{\gamma} \left(\frac{\boldsymbol{\theta}_{i,t}}{\gamma+\boldsymbol{\theta}_{i,t}} \right)^{Y_{i,t}} \right]$

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5 We initially tested the model specification errors, considering such issues as omitted relevant variables and included irrelevant variables, using a bottom-up approaches. The preliminary results indicated that some important variables, such as dummy proxies for a Land-Grant university and the geographic region, could not be included in the KPF because of multicollinearity with the fixed effect model in the panel data analysis. Instead, we adopt an analysis of variance (ANOVA) test using these variables. (See details in the Results section). Since there exist data limitations at the institutional level, we could not include some potentially relevant variables such as the number of authors per paper, full-time equivalents (FTEs), etc.

6 As we mentioned before, generally, there are four different types of university knowledge outputs, including: publication or release into the public domain, public-private collaborations, patenting/licensing, and venture creation. However, in this study, we use only research publications, which represent, by-in-large, the public domain mechanism. (See details in the Data section.)

7 It is comprised of group-variant but time-invariant error term, u_i, and both group and time-variant as idiosyncratic error term, $e_{i,t}$. We assume that they are mean zero, homoscedastic, and exhibit no serial correlation.

8 A type of data in which the observations can take only the non negative integer values {0, 1, 2, 3, ⋯} and where these integers arise from counting rather than ranking.

where r is the dispersion parameter and Γ is the gamma function for the negative binomial MLE. θ is the mean of the negative binomial MLE[9], defined as an unknown parameter.

Since the structure of the KPF model is based on the relationship between research outputs and past research expenditures (Pakes and Griliches 1980 and 1984), so a number of previous studies of the KPF model (see above) have adopted a finite and ad hoc distributed lag model. However, following Crespi and Geuna (2008) and Lee and Graff (2015 and 2017)[10], the relationship between research outputs and past or lagged research expenditures is more likely to follow a polynomial pattern, rather than a geometrically declining (a.k.a. Koyck) pattern. Thus, we adopt a polynomial distributed lag (PDL) structure for the main lag scheme of the research expenditure inputs.

Adapted to equation (1), the PDL model assumes that β can be estimated by a p=0,1,2,..,m degree of polynomial and a j=0,⋯,k lag length, see equation (3). The corresponding equation of m-degree and k-lag length of the unrestricted PDL model is equation (4).

(3) $$\beta_j = \omega_0 + \omega_1 \cdot j + \omega_2 \cdot j^2 + \cdots + \omega_m \cdot j^m = \sum_{p=0}^{m} \omega_p \cdot j^p$$

where ω is a constructed slope coefficient.

(4) $$Y_{i,t} = \alpha + \sum_{p=0}^{m} \omega_p Z_{p,i,t} + \varepsilon_{i,t}$$

and Z is a constructed variable, $Z_{0,i,t} = \sum_{j=0}^{k} j^0 \cdot R_{i,t-j}$, $Z_{1,i,t} = \sum_{j=0}^{k} j \cdot R_{i,t-j}, \cdots$ $Z_{m,i,t} = \sum_{j=0}^{k} j^m \cdot R_{i,t-j}$.

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9 $\boldsymbol{\theta}_{i,t} = E[Y_{i,t}|\boldsymbol{X}_{i,t}] = \exp(\boldsymbol{X}_{i,t}'\boldsymbol{\beta}) = \exp\left(\sum_{i=0}^{N} \beta_j R_{i,t-j}\right)$

10 Crespi and Geuna (2008) introduce the use of the polynomial distributed lag scheme in the knowledge production function context, but they only adopt a linear functional form rather than the count data form of analysis. Lee and Graff (2015 and 2017) combine the count data model with the polynomial distributed lag scheme.

The ω and Z values from equations (3) and (4) are not the true slope coefficients on the original variables. Rather, first, equation (4) is estimated by OLS, and then the true values of the β slope coefficients can are recovered by the following set of equations (5):

(5)
$$
\begin{aligned}
\widetilde{\beta_0} &= \widetilde{\omega_0} \\
\widetilde{\beta_1} &= \widetilde{\omega_0} + \widetilde{\omega_1} + \widetilde{\omega_2} + \cdots + \widetilde{\omega_m} \\
\widetilde{\beta_2} &= \widetilde{\omega_0} + \widetilde{2\omega_1} + \widetilde{4\omega_2} + \cdots + \widetilde{2^m\omega_m} \\
&\vdots \\
\widetilde{\beta_k} &= \widetilde{\omega_0} + \widetilde{k\omega_1} + \widetilde{k^2\omega_2} + \cdots + \widetilde{k^m\omega_m}
\end{aligned}
$$

where the $\widehat{\omega}$ are generated from the OLS procedure, and the $\tilde{\beta}$ are the estimated slope coefficients (For more details, see Gujarati, 2004, pp. 687-691).

The unrestricted PDL model has no *a priori* restrictions, but a restricted PDL model can be limited by restricting the $k+1^{st}$ and greater lagged coefficients to equal zero, which is called a far endpoint restriction. This assumes that unobservable inputs made beyond the k^{th} lag year no longer impact current research outputs, following equation (6):

(6)
$$\beta_{k+1} = \omega_0 + (k+1)\omega_1 + (k+1)^2\omega_2 + \cdots + (k+1)^m\omega_m = 0$$

Equation (6) is substituted into equation (4) and then the model can be estimated by standard OLS procedures. Similarly, the true slope coefficients of the restricted PDL model can be recovered by equation (5), as described above.

2. Data

Table 1 provides summary statistics of these research input and output variables for the 114 U.S. research universities classified as Doctoral Universities-Highest Research Activity in the Carnegie Classification of Institutions of Higher Education[11], also known as "R1 research universities" (For a list of the universities and their rankings, see Appendix 1). The dataset of the research input and output was mainly collected from open resources.

[11] Except City University of New York (CUNY) Graduate School and University Center.

TABLE 1. Summary statistics of all research input and output variables at the 114 U.S. research universities, 1993-2015

	Mean	S.D.	Min	Max	Group	Obs
Research expenditures						
Life science research expenditures*, million $	158.58	163.79	0.62	870.52	114	2,622
Ag & food related research publications**						
All fields	136.83	177.52	0.00	1,129.00	114	2,622
Dairy & animal sciences	13.21	32.37	0.00	304.00	114	2,622
Biotechnology & applied microbiology	37.17	39.27	0.00	398.00	114	2,622
Crop, horticulture, & soil sciences	39.48	66.31	0.00	554.00	114	2,622
Food science and technology	32.29	44.59	0.00	273.00	114	2,622
Regional dummies***						
Pacific (16)	0.14	0.35	0.00	1.00	114	2,622
Mountain (6)	0.05	0.22	0.00	1.00	114	2,622
Northern Plains (3)	0.03	0.16	0.00	1.00	114	2,622
Southern Plains (13)	0.11	0.32	0.00	1.00	114	2,622
Central (20)	0.18	0.38	0.00	1.00	114	2,622
Southeast (25)	0.22	0.41	0.00	1.00	114	2,622
Northeast (31)	0.27	0.45	0.00	1.00	114	2,622
Institutional dummies						
Land-Grant public university (41)	0.36	0.48	0.00	1.00	114	2,622
Non Land-Grant public university (39)	0.34	0.47	0.00	1.00	114	2,622
Non Land-Grant private university (34)	0.29	0.46	0.00	1.00	114	2,622

* Three sub-fields: agricultural sciences, medical sciences, and biological sciences;
** Included in published journal articles, book chapters & reviews, conference paper & proceedings, and scientific letters;
*** See Alston et al. (2010) page 283; Parentheses are the number of universities.

First, the data of university R&D expenditures classified as life sciences as an input was obtained from the Higher Education Research and Development (HERD) Survey of the National Science Foundation (NSF)'s National Center for Science and Engineering Statistics (NCSES) from 1993 to 2015. The life science research expenditures reported by NSF[12] include three sub-fields: agricultural sci-

[12] Because of the limited data reporting in the National Science Foundation, 18 universities' life science research expenditures between 1993 and 1997 were not reported. So, the missing data

ences, biological sciences, and medical sciences. In 2015, the life science research expenditures for the R1 research universities accounted for $28 billion or almost 55 percent of total research expenditures. Within the R1 universities, the life science research expenditures in the Land-Grant universities in 2015 was $10 billion.

The count data of annual research publications as an output was collected from queries for the university affiliation of authors in the ISI Web of Science (Thomson Reuters), covering 1993-2015. Research publications, in which the categories are characterized by published journal articles, book chapters & reviews, conference paper & proceedings, and scientific letters, in agriculture and food related research fields are based on the Web of Science's field categories, and include the following: agriculture dairy animal science, agricultural economic policy, agricultural engineering, agronomy, biotechnology applied microbiology (including bioenergy), crop & horticulture, food science technology, nutrition dietetics, plant science, soil science, agricultural multidisciplinary[13]. Since for some universities there are very few observations in some of these Web of Science field categories, the fields can be merged and classified according to five different research field groups as well as the combination of all agriculturally related fields, as follows: (1) all fields, (2) dairy and animal science, (3) biotechnology and applied microbiology, (4) crop, horticulture, and soil science, and (5) food science and technology.

Finally, universities can be identified as falling within one of seven different multi-state regions of the United States which are chosen, in part, because of broad similarities in agricultural conditions and thus the profile of agricultural industry within each region.[14] Within the 114 sample universities, 41 are Land-Grant universities, which accounts for 36 percent of the total (For a list of the R1 Land-Grant universities, by region, see Appendix 3).

were "back cast" for that earlier period, based on those institutions' total research expenditures for those years, according to the average share that life sciences expenditures represented of total research expenditures as observed for those 18 universities during the middle period of 1998-2002.

[13] Excluded in the natural resource related sub-fields such as forestry, fisheries, etc.

[14] See more detail information in Alston et al. (2010) p.283, but we treat Hawaii as Pacific region.

III. Results

There are two parts to the regression analysis conducted. The first is a panel data analysis of the agricultural knowledge production function (KPF) for the output of research publications in each of the food and agriculture-related research field groups, essentially estimating the system of the universities' production of knowledge that is disseminated via the public domain. The second part involves the analysis of variance (ANOVA), which provides a dummy variable test for the productivity of knowledge production across the different food and agriculture-related research field groups. The main objective of this second analysis is to ascertain how the role of Land-Grant universities affects the production of food and ag related research publications in the various field groupings across the different geographic regions of the U.S.

1. Agricultural knowledge production function

The knowledge production function (KPF) can be defined as the technical relationship between research inputs and outputs. In this analysis, the major knowledge output metric being utilized is the count of food and ag related research publications and the main input measure is annual life sciences research expenditures for 114 U.S. research universities from 1993 to 2015. In this section, we estimate three different agricultural KPF models: (1) a log-log model with an unrestricted polynomial distributed lag (PDL) scheme, (2) a negative binomial MLE model with an unrestricted PDL scheme, and (3) a negative binomial MLE model with a restricted PDL scheme. All three models assume a group fixed effect, preliminarily ascertained by the Hausman test[15], and the optimal degree of the lag structure's polynomial and the lag length in each is chosen based on the information criteria[16].

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15 $H=\left(\tilde{\beta}_{FE}-\tilde{\beta}_{RE}\right)'\left[var\left(\tilde{\beta}_{FE}\right)-var\left(\tilde{\beta}_{RE}\right)\right]^{-1}\left(\tilde{\beta}_{FE}-\tilde{\beta}_{RE}\right)$

16 The Akaike information criterion (AIC), AIC=-2×ln(Likelihood Function)+2×P, and the Schwarz Bayesian information criterion (SBIC), SBIC=-2×ln(Likelihood Function)+ln(N)×p , where p is number of parameters estimated and N is number of observations. The model with the smaller value of the information criterion has a better goodness of fit.

In selecting these three models, we initially tested an *ad hoc* distributed lag scheme of the life science research expenditures, rather than a PDL scheme, across the all three agricultural KPF models. Preliminary test results indicated that, using the *ad hoc* distributed lag scheme, almost all slope coefficients on all lagged years' research expenditures are statistically insignificant. The only significant coefficients were found in the first and last lagged time periods. These results are similar to those found in previous studies (Pakes and Griliches 1980 and 1984; Hausman et al. 1984; Hall et al. 1986; Parday 1989). Subsequent analyses have established that the slope coefficients of the KPF follow a polynomial pattern, so an *ad hoc* distributed lag scheme causes significant model misspecifications (Crespi and Geuna 2008; Lee and Graff 2015 and 2017). Therefore, in this analysis, the PDL is the only lag scheme utilized in the KPF estimations.

1.1. Log-log KPF model

Table 2 shows the results of the panel estimation of the log-log KPF model with an unrestricted PDL scheme of life science research expenditures across the different food and ag related research field groups. There are five different KPF models: model 1 counts all research publications for all fields; model 2 estimates the KPF for just the dairy and animal science publications; model 3 estimates the KPF for biotechnology and applied microbiology publications; model 4, for crop, plant, horticulture, and soil science publications; and, model 5, for the food science and technology publications.

All five models assume a group fixed effect and follow a second degree polynomial with six lagged years of life sciences research expenditures within the PDL structure. Since all are log-log models, each slope coefficient indicates a marginal effect or a *marginal product* of the knowledge production function in the short-run. Most of the slope coefficients in all five models are statistically significant, except the coefficients on the middle range of lagged research expenditures in model 5, from years 2 to 4. The slope coefficients of each model also represent elasticity of output, which is defined as the percent change in current research publications (the output) due to a one percent change in life science research expenditures (the input).

The slope coefficients on lagged research expenditures for models 1, 3, and 5, (all fields, biotechnology, and food science, respectively), follow U-shape or convex patterns whereas for models 2 and 4 (animal science, and crop science, respectively) follow inverted U-shape or concave patterns. We can interpret this to mean that research expenditures have a maximum impact on dairy & animal science publications in the second year and a maximum impact on crop, horticulture, and soil science related research publications in the fourth year.

In Table 2, the sum of the lags represents a long-run or total impact of past and current research expenditures on current year publications. It measures how the research publications at university *i* change in response to changes in life science research expenditures in the long-run. All models have statistical significance at the 1% level, except for model 2, the dairy and animal science field, which has statistical significance at the 10% level. Moreover, the sum of the lags also represents returns to scale of the knowledge production. If the sum of all slope coefficients is less than one, this indicates decreasing returns to scale, when the sum of the lags is equal to one, it indicates constant returns to scale, and a sum greater than one indicates increasing returns to scale.

TABLE 2. Estimates of the log-log model with an unrestricted polynomial distributed lag (PDL) scheme across the different agriculture-related research fields at 114 research universities, 1993-2015

Dependent variable: Research publications (log-log)					
	All fields [1]	Dairy & animal science [2]	Biotechnology & applied microbiology [3]	Crop, horticulture, & soil science [4]	Food science & technology [5]
Group fixed effect	Yes	Yes	Yes	Yes	Yes
Degree of PDL1	2	2	2	2	2
Expenditure_t-0	0.11964*** (0.02980)	-0.08586 (0.16257)	0.13656*** (0.03502)	0.01109 (0.03763)	0.14205** (0.05858)
_t-1	0.09641*** (0.01075)	0.24268*** (0.05809)	0.11938*** (0.01263)	0.05453*** (0.01330)	0.07121*** (0.02073)
_t-2	0.08292*** (0.01606)	0.39606*** (0.08049)	0.11041*** (0.01883)	0.08361*** (0.02095)	0.03112 (0.02982)
_t-3	0.07916*** (0.01989)	0.37427*** (0.10211)	0.10966*** (0.02334)	0.09833*** (0.02582)	0.02178 (0.03773)

(continued)

Dependent variable: Research publications (log-log)					
	All fields [1]	Dairy & animal science [2]	Biotechnology & applied microbiology [3]	Crop, horticulture, & soil science [4]	Food science & technology [5]
_t-4	0.08515***	0.17731**	0.11714***	0.09870***	0.04320
	(0.01527)	(0.08041)	(0.01792)	(0.01954)	(0.02964)
_t-5	0.10088***	-0.19482***	0.13284***	0.08472***	0.09537***
	(0.00991)	(0.04901)	(0.01161)	(0.01281)	(0.01828)
_t-6	0.12635***	-0.74212***	0.15676***	0.05638	0.17830***
	(0.03070)	(0.15033)	(0.03599)	(0.04062)	(0.05570)
Sum of the lags	0.69052***	0.16752*	0.88274***	0.48735***	0.58303***
	(0.01969)	(0.10093)	(0.02296)	(0.02743)	(0.03327)
Mean lag	3.04534	3.74749	3.10674	3.43364	3.29012
Constant	1.18330***	2.74698***	-0.62182***	1.59235***	0.68210***
	(0.08909)	(0.50200)	(0.10476)	(0.12375)	(0.16238)
AIC2	753.88	889.89	1,322.64	418.97	1,184.57
SBIC3	776.14	906.83	1,344.86	438.92	1,205.39
Log-likelihood	-372.94	-440.94	-657.32	-205.48	-588.29
Observations	1,930	510	1,911	1,083	1,346
Groups	114	114	114	114	114

Notes: 1. The number is the degree of polynomial; 2. Akaike Information Criterion; 3. Schwarz Bayesian Information Criterion; Parentheses are standard errors; *** at 1%, ** at 5%, and * at 10% level of statistical significance.

The results of all five models suggest decreasing returns to scale, but with rather different magnitudes of the coefficients. The field of biotechnology and applied microbiology (model 3) has the highest value, at 0.8828 for the sum of estimated coefficients at 1 percent level of statistical significance. The field of dairy and animal science (model 2) has the smallest value, at 0.1675 for the sum of estimated coefficients at 10 percent level of statistically significance. This result indicates that the production of publications in biotechnology and applied microbiology has greater cost advantages than the production of publications in other research fields over the long run.

The mean lag[17] is a weighted average of coefficient values over time and thus represents the average "gestation period" between a research project's inception and completion (see Pakes and Griliches 1980 and 1984; Pardey 1989; Crespi and Geuna 2008). However, in practice, actual expenditures generally begin some time after project inception because of the time involved in applying for and receiving funding (Lee and Graff 2017). The results from model 1 tell us that, for all fields, on average, a university faculty member or research team[18] spends 3.04 years generating a research publication: similarly, in dairy & animal science (model 2), the mean lag is 3.74 years, in biotechnology and microbiology (model 3), it is 3.10 years; in crop, horticulture, and soil science (model 4), it is 3.43 years; and in food science (model 5) it is 3.29 years. Thus, the production of research publications in dairy and animal science has a relatively longer average lag between a research project's inception and completion, while in biotechnology and microbiology, research publications have a relatively shorter average lag.

1.2. Negative binomial MLE of KPF models

Similar to the log-linear KPF model, the panel estimation of the negative binomial maximum likelihood estimation (MLE) of the KPF model PDL schemes of life science research expenditures, but in this case with both unrestricted and restricted versions, across each of the different research field groups (Table 3).

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17 As calculated by this formula, $meanlag = \frac{\sum_0^k k \cdot |\beta_k|}{\sum_0^k |\beta_k|}$. For more details, see Gujarati (2004), pg. 668.

18 According to Wuchty et al. (2007), the traditional university ethos emphasized the role of individual genius in scientific discovery, but in recent developments, most academic research has shifted from an individual model to a teamwork model.

TABLE 3. Estimates of the negative binomial MLE with the unrestricted and restricted polynomial distributed lag (PDL) schemes across the different agriculture-related research fields at 114 research universities, 1993-2015

Dependent variable: Research publications (negative binomial MLE)										
	All fields [1]		Dairy & animal sciences [2]		Biotechnology & applied microbiology [3]		Crop, horticulture, & soil sciences [4]		Food and nutritional sciences [5]	
	Unrestricted	Restricted	Unrestricted	Restricted	Unrestricted	Restricted	Unrestricted	Restricted	Unrestricted	Restricted
Degree of PDL1	2	2	2	3	2	2	2	2	2	2
Expenditure_t-0	0.00062***	0.00052***	0.00022	-0.00089	0.00065***	0.00041***	0.00029	0.00001	0.00108***	0.00090***
	(0.00014)	(0.00011)	(0.00087)	(0.00109)	(0.00016)	(0.00013)	(0.00022)	(0.00016)	(0.00020)	(0.00016)
_t-1	0.00041***	0.00044***	0.00226***	0.00357***	0.00037***	0.00044***	0.00009	0.00017**	0.00055***	0.00059***
	(0.00006)	(0.00005)	(0.00029)	(0.00050)	(0.00006)	(0.00006)	(0.00008)	(0.00007)	(0.00008)	(0.00007)
_t-2	0.00026***	0.00036***	0.00303***	0.00393***	0.00020**	0.00044***	0.00001	0.00028***	0.00017	0.00034***
	(0.00009)	(0.00001)	(0.00054)	(0.00080)	(0.00010)	(0.00001)	(0.00015)	(0.00002)	(0.00012)	(0.00002)
_t-3	0.00017	0.00029***	0.00250***	0.00178***	0.00014	0.00041***	0.00003	0.00034***	-0.00004	0.00015***
	(0.00011)	(0.00003)	(0.00065)	(0.00059)	(0.00012)	(0.00004)	(0.00017)	(0.00005)	(0.00015)	(0.00005)
_t-4	0.00014*	0.00021***	0.00070	-0.00128***	0.00019**	0.00035***	0.00016	0.00034***	-0.00010	0.00002
	(0.00008)	(0.00005)	(0.00048)	(0.00028)	(0.00008)	(0.00006)	(0.00012)	(0.00007)	(0.00011)	(0.00007)
_t-5	0.00018***	0.00014***	-0.00239***	-0.00366***	0.00036***	0.00026***	0.00039***	0.00028***	0.00001	-0.00005
	(0.00006)	(0.00005)	(0.00032)	(0.00054)	(0.00007)	(0.00006)	(0.00009)	(0.00007)	(0.00008)	(0.00007)
_t-6	0.00028	0.00060***	-0.00677***	0.01105***	0.00064***	0.00047***	0.00073**	0.00023***	0.00028	0.00128***
	(0.00019)	(0.00019)	(0.00107)	(0.00367)	(0.00021)	(0.00004)	(0.00030)	(0.00005)	(0.00025)	(0.00027)
Sum of the lags	0.00207***	0.00255***	-0.00045	0.01451***	0.00255***	0.00278***	0.00169***	0.00165***	0.00195***	0.00322***
	(0.00007)	(0.00023)	(0.00034)	(0.00406)	(0.00008)	(0.00010)	(0.00011)	(0.00014)	(0.00010)	(0.00032)
Mean lag	2.23276	2.80184	3.98296	4.07010	2.97350	2.90000	4.22274	3.56629	1.40270	2.91731
Constant	2.48244***	2.48404***	0.91585***	0.91189***	2.17078***	2.16971***	2.84366***	2.84916***	2.33075***	2.33320***
	(0.04724)	(0.04722)	(0.08742)	(0.08794)	(0.05337)	(0.05326)	(0.06956)	(0.06950)	(0.06533)	(0.06528)
AIC2	15,915.79	15,915.16	4,403.31	4,409.57	13,079.88	13,083.83	7,851.94	7,853.53	9,405.85	9,405.71
SBIC3	15,938.07	15,931.87	4,420.25	4,426.50	13,102.12	13,100.52	7,871.91	7,868.51	9,426.71	9,421.36
Log-likelihood	-7,953.89	-7,954.58	-2,197.65	-2,200.78	-6,535.94	-6,538.92	-3,921.97	-3,923.77	-4,698.92	-4,699.86
Observation	1,938	1,938	510	510	1,921	1,921	1,088	1,088	1,360	1,360
Group	114	114	114	114	114	114	114	114	114	114

Notes: 1. The number is the degree of polynomial; 2. Akaike Information Criterion; 3. Schwarz' Bayesian Information Criterion; All model assumes the group fixed effect; Parentheses are standard errors; *** at 1%, ** at 5%, and * at 10% level of statistical significance.

In the unrestricted model, we use a second degree polynomial and the maximum length of the lag is 6 years. Since the slope coefficients of the negative binomial MLE do not directly reveal the marginal effect[19], the values in Table 3 are much smaller than the coefficient values in the log-log KPF model in Table 2. An alternative is to use an incident rate ratio (IRR) for coefficients estimated in the negative binomial MLE of the KPF model for indicating the marginal effect. In Table 3, what is reported are true values of the slope coefficients from the negative binomial MLE regression, not IRR values.

In comparison to the statistical significance of the estimated coefficients in the log-linear KPF model in Table 2, the slope coefficients of the negative binomial MLE in Table 3 are relatively less statistically significant, especially those in models 4 and 5 for crop, horticulture, and soil sciences and food and nutritional sciences respectively, as well as the sum of coefficients in model 2, for dairy and animal sciences. Again, the mean lags in each model can be interpreted to represent the average lag between effective inputs and measured outputs, or the so-called research "gestation" period. These values indicate that changes in life science research expenditures affect research publications 2.23 years later in model 1: similarly, 3.98 years later in model 2; 2.97 years in model 3; 4.22 years in model 4; and 1.40 years in model 5. The lags here are similar to the results of the log-linear model in Table 2, except that here the mean lag for the food and nutritional science research publications is much smaller than in the log linear model, 1.40 years compared to 3.29 years.

In the restricted PDL negative binomial model in Table 3, the degree of polynomial is second order and the maximum length of the lag is 6 years. but the one exception is in model 2, dairy and animal sciences, in which a third order polynomial provides the best fit. As shown in the Empirical Model Framework section, the restricted PDL model known as the end-point restriction assumes that there is no impact beyond 6 years of lagged research expenditures on current year publications. Unlike the results of the unrestricted PDL model in Table 3, most of the slope coefficients in the restricted model in Table 3, are statistically significant, at least at the 5 percent level. Improvements are especially notable in models 4 and 5 compared with the unrestricted models. Although, the restricted PDL model may be too restrictive in some assumptions--it cuts off lag effects beyond 6 years--still, it has meaningful interpretations. One in particular is how re-

[19] Because of the characteristics of log likelihood function and its mean, $E[y_{i,t}|x_{i,t}]=\exp(X'_{i,t}\beta)$.

search expenditures of various lags effects current research publications by comparing the values (magnitudes, signs, statistical significance, etc.) of the slope coefficients between the unrestricted and the restricted PDL models. Another set of meaningful interpretations can come from comparing mean lags between the two sets of models.

In comparing between the unrestricted and restricted PDL models in Table 3, the results of models 4 and 5, the crop, horticulture, and soil sciences and the food and nutritional sciences, respectively, have quite different magnitudes and signs of the slope coefficients, as well as different statistical significance. Research publications in these fields are more likely to be affected by six or more years of lagged research expenditures. Moreover, in model 5, the mean lag of the unrestricted model is much shorter than the restricted model. Finally, we note that the mean lags in the restricted PDL model in Table 3 do not differ from the mean lags in Table 2. Therefore, the mean lags in the negative binomial MLE with a restricted PDL structure can be useful for evaluating the average lag between research project's inception and completion (its gestation period) across the different research fields.

2. The role of Land-Grant universities in agricultural knowledge production and commercial innovation

The main purposes for adopting the analysis of variance (ANOVA) are to explore one of our main research questions, how the Land-Grant status of a university－and therefore its focus on regional economic development－affects its output of research in fields affecting the agricultural industry, and to avoid a multi-collinearity problem with a fixed effect model in the panel data analysis. Using a dummy variable regression, called an analysis of variance (ANOVA) model, we can incorporate the concept of interaction between a quantitative dependent variable and a number of qualitative explanatory variables. The ANOVA can be used to test differences among two or more groups' mean values. The null hypothesis is that the mean values of all group are the same, i.e. that they are not statistically independent.

In this section, there are two different types of ANOVA models: (1) a model with just one qualitative explanatory variable (whether or not a university is a Land-Grant institution) and (2) a model with two qualitative explanatory variables that allows for interaction effects (whether or not a university is a Land-Grant institution, and the geographic region of the university). Equation (7) describes the first ANOVA test, which is based on the pooled-OLS data from 1993 to 2015, with a dummy variable for Land-Grant university status, which is then related to publication output counts across different food and ag related research categories:

$$(7) \qquad Y_i^j = \beta_0 + \beta_1 L_i + \beta_2 Public_i + u_i$$

Where Y = count of research publications related to food and agriculture by authors at university i in research field j

L = 1 if the university is a Land-Grant university

0 if otherwise: non Land-Grant universities (both public and private)

Public = 1 if the university is public, but non Land-Grant

0 if otherwise

Table 4 displays the results of the ANOVA test on the number of research publications by the 114 U.S. research universities in each of the different research field groups, from 1993 to 2015. The test results indicate how the mean number of research publications for each field by authors at Land-Grant universities differ from the mean number of research publications for the same field in the non Land-Grant universities.

TABLE 4. An analysis of variance (ANOVA) model with one qualitative variable for Land-Grant universities, across the different agriculture-related research fields at 114 research universities, 1993-2015

Dependent variable: Research publications					
	All fields [1]	Ag dairy animal science [2]	Biotechnology & applied microbiology [3]	Crop, plant, horticulture, and soil science [4]	Food and nutritional science [5]
Land Grant	222.434***	36.046***	12.281***	91.604***	41.939***
	(6.658)	(1.329)	(1.813)	(2.447)	(1.851)
non Land-Grant (public)	-19.884***	0.710	-15.735***	4.366*	-9.543***
	(6.735)	(1.345)	(1.834)	(2.475)	(1.873)
Constant	63.637***	0.000	38.132***	5.037***	20.468***
	(4.923)	(0.983)	(1.341)	(1.809)	(1.369)
R-squared	0.3991	0.2797	0.0895	0.4183	0.2637
Adjusted R-squared	0.3986	0.2792	0.0888	0.4179	0.2631
F-statistics	869.65***	508.57***	128.74***	941.64***	469.01***
Observation	2,622	2,622	2,622	2,622	2,622

Notes: In order to prevent a dummy variable trap, we are treating the private universities as the benchmark category; Parentheses are standard errors; *** at 1%, ** at 5%, and * at 10% level of statistical significance.

In Table 4, the mean annual number of research publications for all agriculturally related publications from a Land-Grant university is 286.07 per year, which is calculated $E(Y_i \mid L_i=1, public_i=0)= \beta_0+\beta_1$. Similarly, the mean number of total agriculturally-related publications from a public non Land-Grant university is 43.75 per year and the mean number of publications from a private university is 63.64 per year, which can be calculated by $E(Y_i \mid L_i=0, public_i=1)=\beta_0+\beta_2$ and the intercept itself, β_0, respectively. Following these formulae, in the dairy and animal sciences, the mean annual number of research publications by a Land-Grant university is 36.05, but public non Land-Grant and private universities have almost zero. In biotechnology and microbiology, the Land-Grant university's mean annual number of research publications is 50.41, and the public non Land-Grant and private universities' mean annual number of research publications are 22.40 and 38.13, respectively. In the crop, horticulture, and soil sciences, the means are 96.64, 9.40, and 5.04 per year, respectively, and in food and nutritional sciences, they are 62.41, 10.93, and 20.47 per year, respectively.

Overall, the mean number of research publications by the Land-Grant universities is significantly greater than the mean number of research publications in the non Land-Grant universities in these agriculturally related research fields. Particularly, however, in the traditional research fields in agriculture, such as in the dairy and animal sciences or in the crop, horticulture, and soil sciences, the production of research publications by the Land-Grant universities is significantly higher than by the non Land-Grant universities (both public and private). In the biotechnology and microbiology as well as the food and nutritional sciences, the private universities have a remarkably high output of research publications, likely due to the presence of medical schools within many of them.

FIGURE 1. The location of all 114 top-tier (R1) universities in the United States, by Land-Grant and non Land-Grant institutions, broken out into seven geographic regions

In order to consider the importance and influence of geographic location on the relative specialization in agricultural research, the ANOVA test can be extended to include two qualitative variables: (1) the Land-Grant and (2) regional dummy variables. Again, the test is based on the pooled-OLS[20] data from 1993 to 2015. In Figure 1, the universities are classified into seven different multi-state regions—including Pacific, Mountain, Northern Plains, Southern Plains, Central, Southeast, and Northeast—following Alston et al. (2010), recognizing that each region shares broadly similar climactic and agroecological characteristics, and therefore similar profiles of the agricultural industry within the states of that region. Equation (8) represents the interaction effects between the Land-Grant and regional variables.

(8) $$Y_i^j = \beta_0 + \beta_1 L_i + \beta_2 M_i + \beta_3 NP_i + \beta_4 SP_i + \beta_5 C_i + \beta_6 SE_i + \beta_7 \neq_i \\ + \beta_8 (L_i + M_i) + \beta_9 (L_i + NP_i) + \cdots + + \beta_{13} (L_i + \neq_i) + u_i$$

Where Y= count of research publications related to food and agriculture by authors at university i in research field j

L = 1 if the university is a Land-Grant university, 0 a non Land-Grant university

M = 1 if the university is in the Mountain region, 0 otherwise

NP = 1 if the university is in the Northern Plains, 0 otherwise

SP = 1 if the university is in the Southern Plains, 0 otherwise

C = 1 if the university is in the Central region, 0 otherwise

SE = 1 if the university is in the Southeast, 0 otherwise

NE = 1 if the university is in the Northeast, 0 otherwise

Table 5 displays the results of the estimation of the interaction effects between the Land-Grant university variable and the regional variables for the mean annual numbers of research publications by all 114 U.S. R1 research universities, across the different research field groups and geographic regions, from 1993 to 2015. The total number of the Land-Grant universities is 41 in our data sample of 114 universities, (see more details on which regions the Land-Grant universities fall within in Appendix 3 and Figure 1). Similar to the results in Table 4, the mean annual number of research publications across all fields are significantly greater in the Land-Grant universities than the non Land-Grant universities.

[20] Pooled-OLS data can be treated by combining both time series (23 years) and cross-sectional (114 universities) data. Although it is somewhat distinguished from the panel data, the main data set is same in both approaches.

TABLE 5. An analysis of variance (ANOVA) model with two qualitative variables, Land-Grant universities and geographic regions, across various agriculturally-related research fields at 114 U.S. research universities, 1993-2015

Dependent variable: Research publications					
	All fields [1]	Ag dairy animal science [2]	Biotechnology & applied microbiology [3]	Crop, plant, horticulture, & soil science [4]	Food and nutritional science [5]
Land-grant	136.249***	10.194***	-6.422	76.421***	26.519***
	(14.597)	(2.731)	(4.104)	(5.537)	(4.003)
Mountain	-31.228*	0.000	-35.220***	9.080	-5.089
	(18.155)	(3.397)	(5.104)	(6.886)	(4.978)
Northern Plains	-22.087	0.000	-40.209***	13.157	4.965
	(29.647)	(5.547)	(8.336)	(11.246)	(8.129)
Southern Plains	-39.013***	2.770	-41.896***	4.835	-5.957
	(14.824)	(2.774)	(4.168)	(5.623)	(4.065)
Central	-25.330*	0.000	-24.999***	0.008	-0.339
	(14.406)	(2.695)	(4.050)	(5.464)	(3.950)
Southeast	-30.665**	0.000	-32.094***	-1.010	2.438
	(13.769)	(2.576)	(3.871)	(5.223)	(3.775)
Northeast	-7.199	0.000	-17.013***	-4.409	14.222***
	(13.305)	(2.489)	(3.741)	(5.047)	(3.648)
Land×Mountain	-4.890	9.524*	20.324***	-19.910*	-4.095
	(27.612)	(5.166)	(7.763)	(10.474)	(7.571)
Land×Northern Plains	144.403***	44.437***	22.118***	-7.334	22.308**
	(36.218)	(6.777)	(10.183)	(13.738)	(9.931)
Land×Southern Plains	137.779***	45.935***	33.211***	-4.303	44.852***
	(23.032)	(4.309)	(6.476)	(8.736)	(6.315)
Land×Central	225.651***	55.372***	44.576***	34.847***	59.498***
	(19.123)	(3.578)	(5.377)	(7.253)	(5.243)
Land×Southeast	137.019***	34.812***	28.742***	39.060***	13.872***
	(18.647)	(3.489)	(5.243)	(7.073)	(5.113)
Land×Northeast	33.602*	12.061***	21.649***	-4.452	22.243***
	(18.661)	(3.492)	(5.247)	(7.078)	(5.117)
Constant	74.043***	0.000	55.122***	7.713*	11.209***
	(12.103)	(2.265)	(3.403)	(4.591)	(3.319)
R-squared	0.4681	0.4400	0.1408	0.4514	0.3660
Adjusted R-squared	0.4654	0.4372	0.1365	0.4487	0.3629
F-statistics	176.54***	157.65***	32.88***	165.10***	115.82***
Observation	2,622	2,622	2,622	2,622	2,622

Notes: In order to avoid a dummy variable trap, we are treating the non land-grant universities (both public and private) and Pacific region as the benchmark category; Parentheses are standard errors; *** at 1%, ** at 5%, and * at 10% level of statistical significance.

For all fields of agricultural research, the Land-Grant universities in the Central region stand out for having a relatively higher production of research publications than other regions, at 410.61 per university per year.[21] In the field of dairy and animal sciences, the mean number of research publications by Land-Grant universities in the Central region is 65.57 per year, in the Northern Plains, 54.63 per year, and in the Southern Plains, 58.90 per year.

In contrast, it is much lower in the Pacific region, at 10.19 per year; in the Mountain region, at 19.72 per year, and in the Northeast region, at 22.25 per year. However, as noted in the previous ANOVA, the mean number of research publications in dairy and animal sciences by non Land-Grant universities are almost zero, and the current analysis shows that this holds across all regions.

In biotechnology and applied microbiology, the Land-Grant universities in the Central region, again, have the highest production of research publications, at 68.28 per year. In this field, the non Land-Grant universities in the Pacific region have a slightly higher mean number of research publications, at 55.12 per year, than the Land-Grant universities in the Pacific region, 48.70 per year. This can be explained by the fact that this group includes a broad range of biology related topics, such as applied genetics, molecular biotechnology, genomics and proteomics, cell biology, enzymes and proteins, etc., many of which can also be pursued in the medical sciences, and more general biology departments. There has long been overlap between the agricultural life sciences and medicine. In agriculture, biotechnology has long focused on breeding techniques, genetic modification of crops, microorganisms for foods and agricultural products, and bioenergy. Some of the large non Land-Grant universities are on the Pacific coast.

In the field of crop, horticulture, and soil sciences, the mean number of research publications is greatest from Land-Grant universities in the Southeast, at 122.18 per year, but very closely followed, again, by the Land-Grant universities in the Central region, at 118.99 research publications per year. In the Southeast, specialty horticultural crops, such as citrus in Florida and peanuts or peaches in Georgia, are particularly important to agricultural industries of those states. Finally, in the food and nutritional sciences, it is again the Land-Grant universities in the Central region that have the highest mean number of research publications, at 96.89 per year, followed by the Land-Grant universities in the Southern Plains,

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[21] It can be calculated by
$E(Y_i|L_i = 1, C_i = 1) = \beta_0 + \beta_1 + \beta_5 + \beta_{11} = 74.04 + 136.25 - 25.33 + 225.65 = 410.61$

at 76.62 per year, and in the Northeast, at 74.19 per year.

In sum, the two ANOVA models establish that Land-Grant universities certainly do produce farm more research in the agricultural and food sciences than non Land-Grant universities, and among the Land-Grant universities there is some evidence of further specialization within fields of agriculture. We also see that in the Central region, characterized by the "Corn Belt" wherein agriculture is relatively strongest in the United States, the Land-Grant universities there are the largest and therefore tend to dominate the production of research publications across the full range of topics related to agriculture and food.

IV. Discussion and Implications

In this study, we focus on the mission and role of the Land-Grant universities and their sub-institutions－the state agricultural experimental stations (SAESs) and cooperative extension services－in agriculture. The system of the Land-Grant universities and its corresponding policies in the United States are quite unique in the production of agricultural knowledge and dissemination activities. Indeed, the U.S. public and private sectors have been performing the most food and agricultural R&D in the world. Thus, understanding the system and management of knowledge production in the U.S. Land-Grant universities would be significantly meaningful in any country. Indeed, we expect the main context and results of this paper could be applied to the study of the system of food and agricultural R&D and commercial innovation in Korea.

The Korean government has been expanding R&D spending to revitalize the economy in the agricultural sector, encouraging food and agricultural innovation for sustainable growth. However, the system and structures of innovation have been driven by government-led models. According to Lee et al. (2016), public sector agencies and institutions, such as the Rural Development Administration (RDA), Province Agricultural Research & Extension Services (PARES), and Agricultural Technology Center (ATC), are the dominant players in the food and agriculture-related research networks, and they play a central role in the agricultural technology innovation system (ATIS), whereas the private sector industries exhibit only a weak network in the ATIS even though their roles are crucial for introducing commercial innovations in agriculture. Thus, most of the research network is bound up in the public sector, and the structure of the network is more likely to exhibit a hierarchical structure.

The main reasons behind this situation seem to be the different perspectives between public and private sectors. In fact, the public sector most often pursues publicly-oriented objectives, whereas the private sector or industry is a profit maximizer and more often pursues knowledge denominated and disseminated via an intellectual property (IP) based mechanism. Thus, the public sectors' direct collaborations with private sector actors can be somewhat difficult. Interestingly, a university can be a good mediator between public sector and private sector entities, because the research team formations in the modern research universities run like small businesses, or "quasi-firms," optimizing their collective behavior albeit without being directly profit making (Etzkowitz, 2003). They do much more research collaboration with private sector R&D than the public sector does, and conversely, they collaborate more with public sector researchers than industry does. Beyond the traditional dyadic relationships, university research teams often exhibit triadic relationship involving university, industry, and government (a.k.a. the "triple helix"), which is characterized as a dynamic network (Etzkowitz 1993; Etzkowitz and Leydesdorff 1995 and 2000). This conceptualization of the R&D system may suggest an important alternative for the system of agricultural innovation in Korea, in which the system tends to be mostly a one-way or a hierarchical, government-driven network.

Furthermore, universities also provide a good venue for engagement with industry stakeholders, in creating new knowledge that can lead to commercial innovations. While the public sector has played a leading role in Korean agricultural R&D, in the U.S. the private sector has been the largest funder and performer of agricultural R&D. Following Clancy et al. (2016), in 2013, the food and agricultural R&D funding sources from the federal and state governments accounted for \$3.8 billion (23.7 percent) of a total of \$16.3 billion. R&D funding from private sector sources, such as private companies, foundations, and farmer organizations, accounted for \$12.5 billion (76.3 percent). And, while almost all of the private sector R&D funding (\$11.8 billion or about 94 percent) supported R&D performed by private sector organizations themselves, a small but significant portion of private sector R&D funding supported R&D performed by the Land-Grant universities (\$0.7 billion or about 6%). The private sector R&D sponsorship of

R&D in the Land-Grant universities is increasing significantly, even though a large share of the food and agricultural R&D funding still comes from public sponsors in the state and Federal governments (including the USDA, NSF, NIH, etc.), accounting for $2.35 billion of the total $3.04 billion of R&D performed by universities.

Of particular importance in this regard is the potential of university knowledge production activities to affect commercial innovation through various forms of spillovers and collaborations between university, industry, and government. Thus, a deeper understanding of the U.S. Land-Grant system and its R&D activities may have many implications for the system of Korean agricultural innovation in terms of transitioning from government-centered or supplier-led models toward more user-led or network-based models.

Finally, the trends of knowledge production by research field in the U.S. research universities, and especially in the Land-Grant universities, provide important indicators of global trends in food and agriculture-related research for creating a new knowledge and preparing for new directions in industrial innovation. Following the empirical results of this paper, it is clear that the traditional research fields in agriculture, such as dairy or animal science, crop science, horticulture, and soil science have quantitatively a greater volume of output than other research fields. However, in terms of knowledge convergence, these fields show less opportunities for collaborating with non Land-Grant universities, which have the potential to bring new research topics and funding sources, fields such as computer science and data analysis for precision agriculture.

In particular, the biotechnology and applied microbiology research field appears to have greater cost advantages in the long run than other research fields and a shorter mean lag between research project inception and completion. The results indicate that the biotechnology and applied microbiology research field, as related to agriculture and food, is generally overlapping with similar application of the biological sciences in other fields, such as medical sciences and bioenergy. The top-tier private universities as well as a range of industries in the United States are paying attention to these research fields, including technologies like CRISPR-mediated genome editing and analysis of the agricultural microbiome (see more Egelie et al. 2016; Graff and Zilberman 2017). Thus, in terms of opportunity for the creation of new knowledge and commercial innovations in agriculture, the research areas of biotechnology and applied microbiology are more likely to provide potential for sustainable growth in agriculture. Therefore, we expect that these results are a meaningful indicator of where Korean R&D should go and what it should focus on in creating new knowledge and commercial innovations in agriculture.

V. Conclusions

This paper analyzes the knowledge production and dissemination activities of the largest research universities in the United States, specifically in the fields related to agriculture and food, and explores the special role of the Land-Grant universities. In the economy overall, universities conduct 14 percent of total R&D, but in the agricultural and food industries, universities conduct almost 30 percent of R&D. And, considering R&D in just the agricultural sector alone, the share of university R&D is even higher, closer to 50 percent. A large portion of this is due to the role of the Land-Grant universities, which historically have specialized in agricultural and food related research, and the dissemination of that research to stakeholders within their respective regions. Of the 114 Carnegie R1 research universities in the United States, 36 percent are Land-Grant institutions; these Land-Grant universities account for 38 percent of the life sciences research expenditures, but fully 75 percent of the agricultural and food related research publications produced. Yet, we must look at the Land-Grant universities within the context of the larger set of research universities, because the other 25 percent of research publications come from them and because the Land-Grant universities collaborate with and apply scientific discoveries from other universities as peer institutions. We seek to understand how the knowledge production activities of the U.S. university system work together to create a huge repository of new knowledge that is available to enable commercial innovation and technological change within the agricultural and food industries.

The first empirical analysis characterizes the technical relationship between life science research expenditures as an input and agricultural and food related research publications as an output in a knowledge production function (KPF) of all of the 114 top-tier U.S. research universities over 23 years. We utilize three different agricultural KPF models: a log-linear model with an unrestricted polynomial distributed lag (PDL) scheme; a negative binomial maximum likelihood estimation (MLE) with an unrestricted PDL; and a negative binomial MLE with a restricted PDL. Adopting the analysis of neoclassical production theory like returns to scale can be useful for understanding university research productivity. The results of this analysis show that the production of research publications for all food and ag related fields exhibits decreasing returns to scale (DRTS) and among the different fields, biotechnology and applied microbiology appear to have greater cost advantages in the long run. This perhaps follows from the greater overlap, and thus potential spillovers, with medical research and other biological sciences.

The mean lag between research expenditure inputs and research publication outputs indicate the gestation period between a research project's inception and completion. Across the three KPF models, we find the log-linear model and the negative binomial MLE with a restricted PDL are most similar: with the mean lags ranging from 2.90 years for biotechnology and applied microbiology as the shortest, to 4.07 years, for the dairy and animal sciences as the longest. It is clear that the gestation periods or project cycle times vary significantly across field. But, it is also clear that there is a significant lag between changes in research inputs and detectible changes in outputs. One of the major reasons regarding the different nature of the mean gestation lags across sub-fields might be the level of the participation rate of non Land-Grant universities, especially top-tier private universities, which have the potential to bring new funding sources. Moreover, the mean lags can be slightly affected by the journal environments such as the duration and quality of the peer review process across the different journals.

The second empirical analysis focuses on the role of the Land-Grant universities in food and ag related research activities by an analysis of variance (ANOVA). We find that in our sample of the 114 top research universities in the U.S., the Land-Grant universities produce a higher mean number of research publications across all food and ag related fields of research than do the public non Land-Grant universities or the private non Land-Grant universities. Particularly in such traditional agricultural research fields as animal sciences or soil and crop sciences, the mean number of research publications by the Land-Grant universities are much greater than those by non Land-Grant public and private universities.

Finally, looking at the relationship between the geographic locations of universities by region and their profiles of agricultural research we see that the Land-Grant universities in the Central region of the United States or the "Corn

Belt", where agriculture is a relatively more important industry for the region's economy, produce the most food and ag related research publications, averaging 410.61 papers per year. Specifically, for the research field of crop, horticulture, and soil sciences, the Land-Grant universities in Southeast produce slightly more than the Land-Grant universities in the Central region, 122.18 papers per year and 118.99 papers per year, respectively. However, in Pacific region, on average, the non Land-Grant universities produce more research publications for the bio-technology and applied microbiology related fields than the Land-Grant universities. Thus, we interpret this result that the research topics for the bio-technology and applied microbiology can be covered by a variety of research areas, such as medical science, agricultural science, bioengineering and bioenergy, etc., so the non Land-Grant universities, especially private universities, are also highly engaged in these research topics.

At the industry level of agriculture and food, we thus see the interesting dynamic of university R&D and how it contributes to innovation within such a highly regionalized and diffused industry. By having a set of top-tier general research universities with specialized programs in agricultural R&D, namely the Land-Grant universities, the U.S. system achieves three things: (1) The agricultural sciences are maintained as fields of top-tier research, rather than being delegated to a second tier of more vocationally oriented or field work, within the national educational system; (2) Those Land-Grant institutions that are specialized in agricultural sciences and that have the institutional capacity for disseminating new agricultural knowledge dominate in the field, producing the majority of agricultural research publications; (3) Also, as top-tier institutions doing high level research in interesting life sciences and related fields—such as genomics, pathology, epidemiology, population dynamics, etc.—scientists at the Land-Grant universities play a key role of collaborating with scientific colleagues at other non Land-Grant universities, thus enabling the Land-Grant universities to capture spillovers from their peer institutions, the other 64 percent of universities, and applying that knowledge to agricultural problems within their particular regional contexts.

Further, the results of this paper would suggest some insights and implications for the agricultural R&D in Korea: (1) to understand the importance of the Land-Grant system and its corresponding policies for creating a new knowledge and inducing commercial innovation, (2) to realize a university as a good venue for engagement with industry stakeholders, who can lead to commercial innovation, and a good mediator between public and private sectors for achieving collaborative research and triadic research network, and (3) to find potentially commercializable research topics such as the biotechnology and applied microbiology for attaining sustainable growth in agriculture. Thus, these factors would provide some important implications to the system of Korean agricultural innovations for transitioning from government-centered or supplier-led models to user-led or network based models, and suggest a new vision for where the future Korean agriculture should go and what to focus on for creating a new knowledge in agriculture.

In further study, such analysis should take into account other types of university knowledge outputs, such as informally disseminated "tacit" knowledge, formally licensed patents, and startup companies founded by research universities. We expect that the measurement and inclusion of additional research outputs will enable the analysis of them as co-products of the university knowledge production function. Other directions of analysis can explore how private funding affects the productivity of university knowledge production and which knowledge outputs are more highly response to the industry grants and contracts across the different food and ag related research fields.

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APPENDIX 1. The top 114 U.S. universities in the Doctoral Universities-Highest Research Activity in the Carnegie Classification of Institutions of Higher Education by recent 7 years of average number of food and agriculture-related publications (except biotech-related field), covering 2009-2015

University name (rank)	Average number of publications per year	University name (rank)	Average number of publications per year
U. California, Davis (1)	823.0	U. Hawaii, Manoa (48)	56.0
U. Florida (2)	701.6	Emory U. (49)	55.1
Cornell U. (3)	621.9	Duke U. (50)	54.9
Iowa State U. (4)	484.0	U. California, Los Angeles (51)	53.4
North Carolina State U. (5)	468.4	U. Pittsburgh, Pittsburgh (52)	53.3
Washington State U. (6)	465.1	U. Kansas (53)	51.6
U. Georgia (7)	464.7	Boston U. (54)	44.7
U. Minnesota, Twin Cities (8)	433.1	U. California, San Diego (55)	41.1
Michigan State U. (9)	424.7	U. Utah (56)	39.9
U. Wisconsin-Madison (10)	408.1	Florida State U. (57)	37.7
Ohio State U. (11)	377.1	U. South Carolina, Columbia (58)	37.3
Kansas State U. (12)	356.7	West Virginia U. (59)	36.9
U. Illinois, Urbana-Champaign (13)	351.1	U. Texas, Austin (60)	34.6
Texas A&M U., College Station (14)	337.4	Vanderbilt U. (61)	33.4
Purdue U. (15)	334.4	Northwestern U. (62)	30.7
Oregon State U. (16)	319.4	U. Colorado Boulder (63)	28.3
Harvard U. (17)	302.3	U. Southern California (64)	27.4
U. Nebraska, Lincoln (18)	278.3	SUNY, U. Buffalo (65)	26.9
Penn State U. (19)	276.6	Arizona State U. (66)	25.9
U. Arkansas, Fayetteville (20)	267.0	Indiana U., Bloomington (67)	25.7
Virginia Tech U. (21)	252.3	Florida International U. (68)	25.4
Louisiana State U. (22)	249.9	U. Cincinnati (69)	24.3
Colorado State U. (23)	208.9	Brown U. (70)	24.0
U. Missouri, Columbia (24)	200.9	U. Iowa (71)	18.6
U. Tennessee, Knoxville (25)	181.3	U. Oklahoma, Norman (72)	18.3
Rutgers U. (26)	176.4	U. California, Santa Cruz (73)	16.4
U. California, Riverside (27)	167.7	Case Western Reserve University (74)	16.1
U. Kentucky (28)	159.7	U. North Texas, Denton (75)	16.0
U. Massachusetts, Amherst (29)	155.3	George Washington U. (76)	14.7
U. California, Berkeley (30)	139.3	Temple U. (77)	14.1
U. North Carolina, Chapel Hill (31)	136.7	U. Louisville (78)	13.6
Tufts U. (32)	130.9	U. California, Santa Barbara (79)	12.6
Clemson U. (33)	126.3	Georgetown U. (80)	12.6
U. Maryland, College Park (34)	116.4	U. New Mexico (81)	11.6
University of Mississippi (35)	101.9	Northeastern U. (82)	11.6
U. Connecticut (36)	100.0	Wayne State University (83)	11.4
U. Arizona (37)	98.7	Tulane U. (84)	11.0
Texas Tech U. (38)	98.4	U. Miami (85)	10.7
U. Washington, Seattle (39)	97.4	Syracuse U. (86)	10.1

University name (rank)	Average number of publications per year	University name (rank)	Average number of publications per year
Johns Hopkins U. (40)	96.6	U. Wisconsin-Milwaukee (87)	10.0
U. Pennsylvania (41)	95.3	Virginia Commonwealth U. (88)	9.6
U. Illinois, Chicago (42)	74.6	Rice U. (89)	8.7
Yale U. (43)	71.1	Georgia State U. (90)	7.7
Washington U., Saint Louis (44)	68.7	U. Oregon (91)	5.1
Columbia U. (45)	67.7	Boston C. (92)	3.9
U. Delaware (46)	62.9	U. Central Florida (93)	2.0
U. Alabama, Birmingham (47)	57.1	Brandeis U. (94)	1.9
U. Texas, Dallas (95)	1.0	SUNY, U. Albany (105)	0.0
California Institute of Technology (96)	0.0	U. California, Irvine (106)	0.0
Carnegie Mellon U. (97)	0.0	U. Chicago (107)	0.0
George Mason U. (98)	0.0	U. Houston (108)	0.0
Georgia Institute of Technology (99)	0.0	U. Michigan, Ann Arbor (109)	0.0
MIT (100)	0.0	U. Notre Dame (110)	0.0
New York U. (101)	0.0	U. Rochester (111)	0.0
Princeton U. (102)	0.0	U. South Florida, Tampa (112)	0.0
Stanford U. (103)	0.0	U. Texas, Arlington (113)	0.0
SUNY, Stony Brook U. (104)	0.0	U. Virginia, Charlottesville (114)	0.0

APPENDIX 2. The top 114 U.S. universities in the Doctoral Universities-Highest Research Activity in the Carnegie Classification of Institutions of Higher Education by 2015 life science R&D expenditures

University name (rank)	2015 life science expenditures (million $)	University name (rank)	2015 life science expenditures (million $)
Johns Hopkins U. (1)	867.72	U. South Florida, Tampa (34)	295.10
Duke U. (2)	855.98	U. Arizona (35)	289.95
U. Michigan, Ann Arbor (3)	779.92	U. Nebraska, Lincoln (36)	286.06
U. Washington, Seattle (4)	764.57	U. Chicago (37)	276.13
U. Pittsburgh, Pittsburgh (5)	733.93	U. Miami (38)	268.07
U. California, Los Angeles (6)	718.66	Michigan State U. (39)	259.65
U. North Carolina, Chapel Hill (7)	716.71	U. Illinois, Chicago (40)	258.07
U. Pennsylvania (8)	680.07	Boston U. (41)	251.83
Yale U. (9)	665.28	Penn State U. (42)	241.22
Stanford U. (10)	647.80	SUNY, U. Buffalo (43)	238.68
U. California, San Diego (11)	642.37	U. Kentucky (44)	232.83
Cornell U. (12)	631.73	U. Georgia (45)	232.59
Washington U., Saint Louis (13)	617.66	U. Rochester (46)	231.10
U. Wisconsin-Madison (14)	589.65	U. Virginia, Charlottesville (47)	227.65
U. Minnesota, Twin Cities (15)	581.58	Louisiana State U. (48)	225.67
Columbia U. (16)	573.06	U. Illinois, Urbana-Champaign (49)	220.03
U. Florida (17)	539.65	U. California, Berkeley (50)	211.29
Harvard U. (18)	533.23	Purdue U. (51)	209.98

(continued)

University name (rank)	2015 life science expenditures (million $)	University name (rank)	2015 life science expenditures (million $)
Emory U. (19)	530.68	Virginia Tech U. (52)	209.68
U. California, Davis (20)	512.47	North Carolina State U. (53)	208.85
Vanderbilt U. (21)	489.53	U. California, Irvine (54)	195.40
Ohio State U. (22)	473.75	U. Kansas (55)	192.92
U. Alabama, Birmingham (23)	455.48	U. Missouri, Columbia (56)	181.70
Northwestern U. (24)	451.94	Temple U. (57)	169.01
U. Southern California (25)	411.99	Washington State U. (58)	166.58
New York U. (26)	407.73	Virginia Commonwealth U. (59)	164.14
Rutgers U. (27)	366.18	George Washington U. (60)	159.22
U. Cincinnati (28)	347.13	Wayne State University (61)	157.21
Case Western Reserve University (29)	340.04	Iowa State U. (62)	149.39
U. Utah (30)	326.55	U. Connecticut (63)	143.53
Indiana U., Bloomington (31)	323.49	U. New Mexico (64)	141.88
U. Iowa (32)	322.02	U. Louisville (65)	135.97
Texas A&M U., College Station (33)	320.56	Brown U. (66)	135.23
MIT (67)	129.16	Princeton U. (91)	41.46
Georgetown U. (68)	128.58	Georgia State U. (92)	40.30
U. Oklahoma, Norman (69)	127.53	Clemson U. (93)	39.59
Oregon State U. (70)	122.70	Texas Tech U. (94)	36.13
Kansas State U. (71)	122.68	Northeastern U. (95)	34.16
Colorado State U. (72)	122.50	Florida State U. (96)	34.01
U. Hawaii, Manoa (73)	121.74	Brandeis U. (97)	30.61
Tulane U. (74)	117.78	U. Oregon (98)	30.39
U. Maryland, College Park (75)	115.90	U. Notre Dame (99)	26.99
U. South Carolina, Columbia (76)	111.13	U. Central Florida (100)	26.90
Tufts U. (77)	110.86	U. Colorado Boulder (101)	26.76
West Virginia U. (78)	96.10	U. Houston (102)	24.34
SUNY, Stony Brook U. (79)	88.61	U. California, Santa Barbara (103)	24.09
U. Massachusetts, Amherst (80)	81.17	U. California, Santa Cruz (104)	22.71
Arizona State U. (81)	77.87	U. Texas, Dallas (105)	21.14
SUNY, U. Albany (82)	75.67	Georgia Institute of Technology (106)	19.88
U. California, Riverside (83)	75.62	George Mason U. (107)	18.43
U. Arkansas, Fayetteville (84)	75.20	U. Texas, Arlington (108)	16.08
U. Texas, Austin (85)	74.07	Rice U. (109)	11.82
U. Tennessee, Knoxville (86)	66.44	Carnegie Mellon U. (110)	11.21
U. Mississippi (87)	64.63	U. Wisconsin-Milwaukee (111)	11.08
California Institute of Technology (88)	63.91	U. North Texas, Denton (112)	8.88
U. Delaware (89)	58.33	Boston C. (113)	7.09
Florida International U. (90)	41.71	Syracuse U. (114)	6.96

APPENDIX 3. The location of 41 Land-Grant universities ranked as R1 Doctoral Universities-Highest Research Activity in the Carnegie Classification of Institutions of Higher Education, by region of the United States

U.S. Regions	Universities
Pacific (11)	Oregon State U.; U. California; Berkeley; U. California; Davis; U. California; Irvine; U. California; Los Angeles; U. California; Riverside; U. California; San Diego; U. California; Santa Barbara; U. California; Santa Cruz; U. Hawaii, Manoa; Washington State U.
Mountain (2)	Colorado State U.; U. Arizona
Northern Plains (2)	Kansas State U.; U. Nebraska, Lincoln
Southern Plains (3)	Louisiana State U.; Texas A&M U.; U. Arkansas, Fayetteville
Central (8)	Iowa State U.; Michigan State U.; Ohio State U.; Purdue U.; U. Illinois, Urbana-Champaign; U. Minnesota, Twin Cities; U. Missouri, Columbia; U. Wisconsin-Madison
Southeast (8)	Clemson U.; North Carolina State U.; U. Florida; U. Georgia; U. Kentucky; U. Tennessee, Knoxville; Virginia Tech U.; West Virginia U.
Northeast (7)	Cornell U.; Penn State U.; Rutgers U.; U. Connecticut; U. Delaware; U. Maryland, College Park; U. Massachusetts, Amherst

Note: Parentheses are the number of universities.