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MAKING TIME FOR AGRICULTURAL AND LIFE SCIENCE RESEARCH: TECHNICAL CHANGE AND PRODUCTIVITY GAINS

DANIEL L. PRAGER, JEREMY D. FOLTZ, AND BRADFORD L. BARHAM

This work analyzes the research productivity of agricultural and life science faculty in U.S. Land Grant research universities from 1975 to 2005. Production function estimations that control for inputs and demographic characteristics reveal significant improvements after 1980 in faculty research productivity per unit time, especially in the non-top ten universities. Because, however, time available to faculty for research has decreased substantially in the past three decades, overall journal article output per faculty did not increase after the 1980s. Our findings demonstrate large productivity increases but raise concerns about the optimal allocation of faculty time.

Key words: Faculty research productivity, production function estimations, technological change, faculty time allocation.

JEL codes: I23, Q10, O30.

Studies of research at U.S. Land Grant institutions celebrate a long and storied history of scientific discovery, public good creation, and high social returns (see, e.g., Fuglie and Heisey (2007) and Alston et al. (2010) for overviews). In one recent example of that literature, Huffman and Evenson (2006) show the rate of return to public resources invested in agricultural research is between 49% and 62%. While changes in the last two decades have increased the importance of privately captured research patenting and commercially propagated research (see, e.g., Foltz, Kim, and Barham 2007; Just and Huffman 2009), the primary mechanism for the dissemination of knowledge for U.S. Land Grant universities has been and continues to be publicly available research publications: journal articles, books, research reports.

The continued production of these public research outputs is a key metric of a successful agricultural (and scientific) research system. How efficiently Land Grant universities produce these research outputs and how research productivity may have changed over time are important questions for understanding the future of agricultural and life science research in the United States.

This article investigates the evolution of U.S. agricultural and life science faculty research performance in producing journal articles spanning three decades, 1975–2005. The primary focus is on how changes in time allocation and other key inputs to research shape faculty and university research productivity. We exploit data collected from agricultural and life scientists at U.S. Land Grant universities in four random-sample surveys, which also included a longitudinal sub-sample for the last two periods. Our empirical analysis takes advantage of both the repeated cross-sections and the panel to demonstrate the robustness of the following main result: U.S. agricultural and life science faculty have become more productive, across various measures of research output, while their time for research has contracted significantly. The net effect is a steady level of public research output over most of the time period despite less time for science.

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The authors declare no conflicts of interest with respect to this work.

The combination of repeated, cross-sectional, and panel data in this study permit the construction of comparable measures of the factors influencing research performance among a critical subset of U.S. research faculty and create the opportunity to study the evolution of individual faculty experiences over time as well. The empirical analysis tracks dynamic population level changes in research inputs and outputs as well as addressing endogeneity and other specification issues that arise in efforts to identify the factors shaping individual research productivity outcomes. What distinguishes this study from previous empirical examinations of faculty research performance is the opportunity to incorporate “time for science” measures explicitly into the analysis in a consistent manner over a significant time span.

Past aggregate level research has investigated the many influences and incentives affecting academic scientists’ productivity (see, e.g., Foltz et al. 2011; Stephan 2012); addressed the increase in incentives for faculty to compete for grants increasingly from National Science Foundation, National Institutes of Health and private sources rather than USDA (e.g., Huffman and Evenson 2006; Alston et al. 2010); and explored the increase in commercial opportunities, which may be synergistic with, or detract from, time devoted to public science (e.g., Sampat 2006; Foltz, Kim, and Barham 2007; Thursby, Fuller, and Thursby 2009). Only Harter, Becker, and Watts (2011) have done something similar for academic economists, with more of an emphasis on the allocation of time across research and teaching activities than on the evolution of research productivity outcomes and how they relate to a broader suite of time measures.

This study identifies three broad empirical regularities. First, measured in articles (and broader research outputs) per unit of time, faculty productivity has grown significantly from the 1970s to the early 2000s, especially in the non-top ten Land Grant research institutions. These findings on research productivity dynamics are consistent with the Agrawal and Goldfarb (2008) study of the impacts of the expansion of the internet and computational opportunities on U.S. faculty research performance in middle-tier research institutions. A second is that while most other key research inputs have stayed relatively constant (with some minor fluctuations), computational resources have

increased and faculty “time for science” has declined significantly over time across almost all cohorts (Barham, Foltz, and Prager 2014). The main explanation for this decline in time for science has been a commensurate expansion in the proportion of time that faculty spend on administrative duties, both general ones and those related to pre- and post-grant responsibilities. Teaching time has not varied across the study period. The third finding is that, while these productivity and time trends vary some by fields of study and by type of university, they are secular, widespread trends, which points to the potential value of broader policy consideration of whether faculty time allocation outcomes are in optimal alignment with respect to opportunity costs.

The remainder of this article is organized as follows. The next section is a selective review of the recent literature on faculty research performance that highlights key contextual, empirical, and methodological issues. Following is a summary of the data available for the analysis and its main features that shape and constrain the empirical analysis. The third section describes our empirical approach to studying faculty research performance, including the primary count-data regression specifications used to exploit the panel and pooled cross-sectional data sources. The fourth section presents the results, and the final section concludes with a reflection on the scientific and policy implications of the principal findings.

Faculty Research Productivity in the Literature

Both at the individual and university level, technical change over the last four decades has been a major factor in shaping the nature and rapidity of the publication of journal articles by university researchers. Especially since the late 1980s, advances in computers and software have provided ever expanding, ready-access computing capacity and data analysis at low cost (Moore 1975). Research professors throughout the United States (and the world) have today easily available data processing, information management, and communication options that were unimaginable in the early 1980s and still in their relative infancy in the early to mid-1990s. An array of related and complementary life science research tools (e.g., the gene

gun; genetic sequencing, image resonance technologies; nano-sensory devices) have combined to create the potential for significant growth in the quantity (and quality) of scientific output by university faculty in life-science related fields. This opportunity has in turn motivated large public and private investments in life-science research facilities and initiatives across the country and around the world (Owen-Smith et al. 2002; De Vol and Bedroussian 2006). At the same time, agricultural researchers have experienced a major shift in their funding environment with the decline of formula funds and the substitution and expansion of major competitive federal grant opportunities (Just and Huffman 2009).

Initial empirical evidence from the rest of the economy had at first suggested that productivity improvements associated with computers were lower than expected and took considerable time to achieve. Two leading studies in the 1990s, including one by a team of scientists at the National Research Council, described a “productivity paradox” of widespread diffusion of computers associated with little growth of productivity (Harris 1994; Landeaur 1995). One potential explanation of the productivity paradox was time shifting in which computerization merely shifted worker tasks without making them more productive (Landeaur 1995). More recently, longer term studies have found convincing evidence in the U.S. economy of a significant productivity gain due to computers and other technologies (Jorgenson, Ho, and Stiroh 2003; Jorgenson, Ho, and Stiroh 2008; Bloom, Sadun, and Van Reenen 2012), but debate continues over the degree to which computers and other new technologies affect productivity of service sector work (Licht and Moch 1999). Relatively little empirical work has investigated such productivity questions at the individual worker level; most micro-economic productivity studies instead analyze sector or firm-level data to study returns to capital invested in computers.

Despite its potential importance, the literature has not explicitly investigated the effect of actual research time as an input to faculty productivity. Time considerations are implicitly built into the analysis of tradeoffs or synergies across research activities (e.g., Foltz, Kim, and Barham 2007) or types of research, but overall research time measures typically have not been included in previous studies. The unique feature of our data set is

that it directly measures the proportions of faculty time allocated to research, teaching, administration, and outreach. Other research has found that endowment shocks, such as stock market declines and public funding cuts, can lead universities to trim administrative support staff throughout campus (Brown et al. 2010), which could increase the administrative duties of faculty. But, as far as we are aware, prior to this article, actual impacts of these changes in time available to faculty have not been explicitly captured in analyses of university research productivity.

Rather than focusing primarily on whether funding incentives are changing the output mix (and in effect diminishing time) devoted to open science research production, our work explicitly examines faculty time allocation and how it affects the research output of individual university faculty over a thirty-year period from 1975 to 2005. If funding incentives were in fact changing the output mix, it would imply lower productivity for publicly available research outputs such as journal articles per unit of input, in particular labor inputs. Our work described below also analyzes the potential effects on journal article production of changes in incentives between different types of faculty efforts: teaching, grant getting, and research quality.

Data and Selected Key Descriptive Statistics

The data analyzed in this work come from four random sample, representative surveys of agricultural and life scientists on the faculty of 1862 Land Grant universities. Surveys were conducted in 1979, 1989, 1995, and 2005.¹ The researchers drew sample frames for the cross-sectional surveys randomly from available lists of faculty in colleges of agricultural and life sciences at all of the 1862 Land Grant universities in the country; the first three were from a USDA printed directory and in 2005 from the web sites of each university and member departments. Appendix tables 1 and 2 provide a list of universities and departments included in the survey.

In addition to the cross-sectional data, a panel of respondents from 1995 was resurveyed in 2005. The panel is based on

¹ See Busch and Lacy (1983) for a description of the 1979 survey; Buttel (2001) for a description of the 1989 and 1995 surveys; and Goldberger et al. (2005) for a description of the 2005 survey.

Table 1. Research Output and Research Inputs, 1979–2005

		Sample Year			
		1979	1989	1995	2005
<i>Panel A: Research Inputs</i>					
Actual Time Spent	Research (%)	60.2	58.2	52.4	45.9
	Teaching (%)	28.6	24.9	30.1	29.1
	Admin (%)	4.7	7.3	5.8	9.3
	Extension Appt. (%)	5.6	7.9	8.6	14.5
Research (%)	Top-ten schools	60.8	59.8	53.3	45.4
	Not Top-ten	59.1	55.5	50.1	47.2
Research Time	Grant Preparation (%)	–	–	13	20
	Administration (%)	–	–	14.6	21.6
	Doing Research (%)	–	–	71.6	58.4
Adjusted Actual Research Time (%)		–	–	37.6	26.7
Inputs	Grad students	2.73	2.47	2.85	2.38
	Post docs	.17	.38	.4	.43
	Technicians	1.39	1.17	1.3	1.14
	Research Budget (\$1000)	180	152	137	168
<i>Panel B: Research Outputs</i>					
Journal Articles	Full Sample	12.2	13.1	12.6	13.1
	Top-ten schools	14.2	15.6	14.4	14.6
	Not Top-ten	11.2	11.8	11.9	12.5
Output^a	Full Sample	13.7	15.1	15	15.4
	Top-ten schools	16	18.1	17.5	17.1
	Not Top-ten	12.5	13.4	14.1	14.7
<i>Panel C: Sample Composition</i>					
Demographic	Assistant Prof. (%)	14.6	20.2	13.1	19
	Associate Prof. (%)	26	27.9	26.9	27.4
	Full Prof. (%)	59.3	51.6	60	53.6
	Years since PhD	16.8	16.3	18.9	19.6
	Female (%)	4.5	7.5	5.5	18.4
Disciplines	Animal Science (%)	19.7	22.7	16.4	15.2
	Plant Science (%)	57.9	59.4	52	49.8
	Env. Science (%)	11.9	7.6	23.3	21.3
	Food Science (%)	9.2	7.5	6.6	13.8
	Other (%)	1.3	2.8	1.8	0.0

^aOutput is calculated according to the formula: Output = 1*(journal articles) + 3*(books) + 0.75*(book chapters) + 0.5*(edited books).

a representative sample of professors from 1989 who were resurveyed in 1995.² In 2005, each active member of the 1995 panel was contacted and asked to participate in the latter survey. We use a consistent balanced panel of 147 faculty who responded in both years.³

² Although the panel data collection began with the 1989 survey, we lack identifying information for that year and cannot include it in our analysis. Additional respondents were added from a random draw in 1995 to replenish the panel, maintain a similar age structure, and replace those who had exited academia.

³ There were a total of 259 faculty who responded to the panel survey in both 1995 and 2005. We discarded pairs of observations for respondents who did not record their 5-year budget, their allocation of research time, journal articles produced, or years

The first three surveys (1979, 1989, and 1995) were mailed to respondents with the last one (2005) conducted using a web-based interface with email and paper mail reminders. The later rounds of surveys

since PhD. In order to maintain as many as possible of the remaining observations, the following assumptions were made: (1) faculty who only reported post-docs or graduate students from one of the years were assumed to have the same number for the other year; (2) it was assumed that there was no extension appointment if that value was missing. Finally, to make results consistent with the cross sectional analysis, we include only data from the same disciplines used in that analysis. This left a fully balanced panel of 147 individuals. The key results presented in this article are un-changed by expanding the sample to the full 259 faculty observations available.

repeated questions from previous surveys in order to provide comparisons over time and similar content across years.⁴ Response rates ranged from a high of 76% in the 1979 survey to a low of 57% and 58% in 1995 and 2005, respectively. Sample sizes varied, but in the cross-section econometric analysis reported on below we use the following number of observations for each year: 1979, $n = 553$; 1989, $n = 777$; 1995, $n = 275$; 2005, $n = 647$. None of the panel data are included in the cross-section data. The 2005 survey respondents showed no significant differences in demographics from nonrespondents using demographic information that could be gleaned from CVs and other information available on the web about nonrespondents. We are not aware of any nonresponse bias tests on the earlier surveys and are unable to test for such.⁵

Questions in these surveys document research inputs and outputs as well as the demographics and the disciplinary focus of the individual respondent. On the research output side, respondents provided the number of journal publications they had produced over the previous five years as well as a range of other types of research outputs (such as: Ph.D. and Masters students graduated, book chapters, extension publications, and in the 2005 data, patents and invention disclosures). For our measures of research productivity, we compare the number of published scientific articles with no adjustments for quality along with a composite measure of published output.⁶ A robustness check described below using the 2005 data shows that adjusting for the relative number of citations to an article does not significantly change the key coefficients of interest.

⁴ Electronic versions of the survey instruments are available from the authors upon request.

⁵ Faculty responses came from a range of departments including physical and biological sciences, engineering, biochemistry, and social science. However, the only disciplines that were present in all four of the surveys include animal science, environmental science, food science, and plant science. We therefore exclude engineering, biochemistry, and social sciences faculty from the analysis below. An analysis that includes those fields yields the same key results as presented in this article, but is not presented due to concerns about biases from year-to-year sample inconsistency. Results are available from the authors upon request.

⁶ We also omit patent production, which would only add to the research productivity estimates given recent growth in patenting activity especially in the life sciences (Foltz, Kim, and Barham 2007; Azoulay, Ding, and Stuart 2009; and Chavas et al. 2011). Our data do show that faculty in the 2005 survey with the intent to patent are 12% more productive than faculty who do not intend to patent. These results are available from the authors upon request.

On the research input side, faculty provided their average annual research budget for their lab or shop for the previous five years, as well as the number of graduate students, post-docs, and technicians who worked for them in the past year. Data for research budgets were converted into constant 2000 dollars using the Huffman-Evenson Agricultural Research Price Index.⁷ In the section on time allocation, faculty supplied their formal appointments and how they actually divided their time in a typical week during the year between research, administration, extension and outreach, and instruction. For the years 1995 and 2005, respondents further divided their research time between that spent on grant preparation, research-related administrative activities, and actively doing research. Combined, these output and input measures, with both repeated cross-section and panel samples, provide a unique opportunity for focusing on the evolution of research productivity and time for science, while controlling for other key inputs.

We should, however, note some limitations of the data that shape our econometric modeling strategy and variations in specification. First, we only have consistent measures of the percentage of time allocated to research, rather than the actual hours spent. If the hours that faculty work each week has changed substantially over time, this could bias the results. Second, to account for the natural spikes in research output and budgets, data for these measures were collected for the five years before the survey, while in contrast our measures of time and other key input data are from the previous year. We do not believe this biases the results significantly since most of these variables are fairly consistent over a period of five years.⁸ Finally, in our main results, our analysis is subject to the standard critique that the intrinsic ability of the researcher is unobservable. The 1995–2005 panel data, however, allow us to control for individual faculty-level unobservables, such as innate ability and variation in how they answer survey questions, through fixed effect estimation methods.

⁷ The Huffman and Evenson Agricultural Research Price Index (see Huffman and Evanson 2006, p. 105) is based on the costs of total real private and public agricultural research expenditures. The authors of the index provided expanded data for the years up to 2005 for this research project.

⁸ In 2005, the only year for which we have both measures, the correlation between the lab budget for the last year and the average of the budget for the last 5 years is 0.77.

As demonstrated below, the main results are consistent across the repeated cross-section analysis and the panel fixed-effect estimates.

Key descriptive statistics

The panels in table 1 show variable means for the cross-sectional data for both inputs and outputs of the research production process. The time allocation measures in panel A show the percentage of actual time that faculty reported spending on the following activities: research, teaching, extension, and administration. The first thing to note is that panel A documents a large, secular decrease in the proportion of time available for research across all years from 60% in 1979 to 47% in 2005. This holds true across elite and nonelite universities, by tenure status and discipline, and among men and women. Furthermore, the proportion of time dedicated to “pure” research, rather than grant preparation or other administration, has decreased substantially from 38% in 1995 to 27% in 2005.⁹ Conversely, administration and extension activities were the primary activities where faculty time shares increased substantively. While the increase in administrative time is due to increases in both the intensive (more time) and extensive (more faculty) margins, the growth in extension time is almost entirely due to increases in the percentage of extension appointments for those who had extension appointments. Teaching time efforts are not significantly different from year to year, remaining effectively constant.

Panel A also demonstrates trends in the other key inputs into faculty research: graduate students, post-docs, and technicians who work in labs and research budgets to fund those labs. Over the same thirty-year period, inputs into research aside from faculty time have fluctuated but in net have remained fairly constant. Graduate students per researcher averaged around 2.6, with a high of 2.85 in 1995 and a low of 2.38 in 2005. The biggest change has been an increase in post-doctoral researchers, which more than doubled from 0.17 per lab to 0.38 per lab from 1979 to 1989 and then continued a small nonsignificant increase after 1989.

⁹ Research time changes are statistically significant across almost all subgroups. See Barham, Foltz, and Prager (2014) for a detailed disaggregation and discussion of these trends.

Real research budgets varied slightly but for the most part not statistically significantly. They did dip 24% between 1979 and 1995 but nearly returned to 1979 levels in 2005 in constant dollar terms.

Despite relatively constant research dollars overall, the data show large changes in funding sources for agricultural and life scientists between 1989, 1995, and 2005 (the 1979 survey contains information on funding amounts but not sources). Between 1989 and 2005, the proportion of research monies from formula funds was cut in half (40.3% to 20.9%), while competitive research funding more than doubled (12.6% to 30.7%) even while the real value of research funding has stayed mostly constant. At the same time, across all disciplines, federal funding rose only moderately from 61% in 1989 to 67% in 1995 and 2005.¹⁰ This trend is widespread: the rise in competitive funding and decrease in formula funding affects every disciplinary field without exception. In some fields the increase has been even more dramatic; for example, in the food science field, competitive funding soared from 9% of total funding in 1989 to 36% in 2005.

Trends in research outputs are displayed in panel B. Research article output has remained remarkably consistent at twelve to thirteen articles per faculty per five-year period, varying by a nonsignificant amount from year to year. The composite output measure,¹¹ which includes articles, books, book chapters, and edited books, shows a nearly identical trend, rising slightly from 1979 to 1989 then staying constant from 1989 to 2005. Among top-ten universities, as shown in panel B, journal article production fluctuated between 14.2 and 15.6 articles throughout the sample, while for non-top ten schools journal article production was consistently 25%–30% lower than at top ten schools.¹² Though not shown, after 1979 average journal article production varies

¹⁰ An exception is social sciences, where federal funding decreased from 81.4% to 72.2% between 1995 and 2005. However, since we do not have data for 1989, this discipline is not included in the regressions.

¹¹ The output variable is calculated as: $\text{output} = 1 * (\text{journal articles}) + 3 * (\text{books}) + 0.75 * (\text{book chapters}) + 0.5 * (\text{edited books})$.

¹² For the years 1979 to 1995, top ten status was determined by ranking land grant universities based on three criteria: (1) total State Agricultural Experiment Station research expenditures in 1992, (2) the number of doctorates granted in “agricultural sciences” in 1995, and (3) the number of doctorates granted in “biosciences” in 1995. An overall index calculated by equally weighting these three items for each land-grant university. For 2005, top ten status was determined by ranking land grant

little within assistant, associate, or full professors categories. Taken at face value, such stagnant output production in a period of substantial technological change in life sciences technologies would be consistent with a productivity paradox, if not for the decrease in time for science.

Finally, panel C shows the composition of the sample for each survey year by demographic elements and research disciplines. Each year, associate professors comprise just over one-fourth of the sample. However, due to random sampling variation, the proportion of assistant and full professors varies by up to seven percentage points from year to year. Over the three decades in which the survey was conducted, the sample aged 2.5 years, became markedly more female, and reflects a steady increase in the average percentage of time dedicated to extension activities.

Framework and Econometric Model

The combination of steady research output and decreasing time for science suggests a sharp rise in research productivity; however, to so conclude, one must also account for potential changes in other inputs such as levels of funding, post-docs, and graduate assistants. There are several key inputs to the production of university scientific research: faculty members contribute their own time, delegate tasks to graduate students and post-docs, and need sufficient funding to carry out research. Land Grant university faculty output is multifaceted, producing public research (journal articles, books, abstracts, etc.), private research (consultancies, patents, etc.), teaching output (trained undergraduate and graduate students), and extension/outreach. We focus on the production of a single output, public research, while taking care to account potential biases from changing incentives for other outputs.¹³

universities based on the Faculty Scholarly Productivity Index of top performing individual programs.

¹³ We would ideally like to place these activities in a multiple-input multiple-output model where we could fully account for all the work product of faculty, including public research output (e.g., books and journal articles), private research output (e.g., patents and commercialization activities), and teaching. Outside of public research, however, we lack consistent data on these outputs across years. While this necessarily produces a partial output measure, the biases we expect would push our results toward zero. Teaching time has remained constant over time and, while the potential to patent has increased substantially, days of

The production function for faculty output can be written as $Y = A * F(L, X; Z)$, where Y is output (e.g., journal articles); L is the amount of a faculty's labor time in research; X represents other inputs, including capital budget; Z are demographic controls; and A is the standard Solow residual, a measure of average factor productivity.¹⁴ We are interested in two potential phenomena, increases in average factor productivity, A , and changes to the productivity of individual factors of production, faculty labor in particular. Since we are unable to measure " A " directly, we employ the standard approach, which allows us to identify changes in average factor productivity (AFP) over time. At the same time, an estimation of the interaction between labor inputs and time dummies allows for a test of the relative productivity of an additional input of labor in specific years. A straightforward way to test for changes in productivity is to use an equation of the form:

$$(1) \quad Y = \phi + \theta T + \gamma_1 L + \gamma_2 (L * T) + X'\beta + Z'\delta + \epsilon.$$

To measure changes in average factor productivity (AFP), after controlling for labor inputs (L), other inputs and controls (X), and individual demographic factors (Z), we can test the significance of θ , the coefficient on a series of time dummies (T). In terms of labor productivity, $L * T$ is a switching variable capturing labor productivity changes over time and our coefficient of interest is γ_2 , which measures how the marginal product of labor changes over time.

While we also do regressions on a composite research output measure, our main dependent variable, the number of journal articles written in the past five years, is subject to some criticism, since we observe neither the number of coauthors nor the quality of the article. If faculty respondents are publishing more articles in "easier" journals; or the well-documented increase in coauthorship requires less output per author; or, if the overall number of journals has increased—thereby making publishing

consulting has remained a negligible average of 3.5 days across the sample years. By not measuring patents and other commercial outputs beyond consulting, we would tend to under-estimate the effects of research time on output, biasing our results toward zero.

¹⁴ Since we are estimating a production function for one of the multiple outputs in the production process, this measure is average factor productivity rather than total factor productivity.

easier, our productivity measures would be biased upward.¹⁵ There are, however, several countervailing forces that suggest it could be harder to publish in 2005 than in 1979. First, many journals, especially top journals, have become more selective, rejecting a higher proportion of articles.¹⁶ Second, as more international scientists publish in U.S. and European journals, there is a larger pool of authors vying for these same spots in journals. Arguably, as demonstrated by Jones (2009), there is also an increased “burden of knowledge,” which makes innovation and innovative journal articles more difficult.

A third issue is that since we cannot measure quality, secular changes in the quality of articles over time might bias our labor productivity and technological change results. The aggregate Land Grant university data from 1981 to 1998 used in Foltz et al. (2011) show a 5% and statistically significant positive increase in relative citations rates per article that mirrors a similar increase from other major research universities.¹⁷ Also where Foltz, Kim, and Barham (2007) presents results for quantity and quality adjusted measures of agricultural research together, the quantity measures provide the same inference as the quality adjusted measures. Thus we expect at most a small downward bias in our estimates because we are not fully accounting for quality differences. With these potential countervailing arguments in mind, the use of publication counts as a measure of output is well established in the literature, and we have consistent data across a number of years to identify the effects of research inputs (including time) on research output.

Count Data Model in the Cross-Section Data

In order to account for a discrete integer dependent variable, the regressions use a count data framework. Of the various count data models available, Poisson and negative binomial models are most frequently used

for this type of analysis. Within our data, the sample mean (12.82) of journal articles is significantly lower than the variance (132.2), which could result from a long upper tail to the distribution caused by a small percentage of “star” faculty producing large numbers of publications.¹⁸

The standard mathematical notation for a negative binomial model is as follows:

$$\begin{aligned} y_i &\sim \text{Poisson}(\mu_i) \\ \mu_i &= \exp(\mathbf{x}_i\boldsymbol{\beta} + \epsilon_i) \\ \exp(\epsilon_i) &= \text{Gamma}\left[\frac{1}{\alpha}, \alpha\right] \end{aligned}$$

where y is our measure of research output, $\mathbf{x}$ is a vector of input variables including capital and labor, and α provides the overdispersion parameter that adjusts the Poisson model into a negative binomial regression. The negative binomial framework estimates dispersion as $V[y_i|\mathbf{x}_i] = \mu_i + \alpha\mu_i^p$ where p is specified and α is an estimated parameter of the model. In this analysis, we employ the widely used option where $p=2$ (the NB2 model). Our results, however, are robust to alternate specifications of the negative binomial model and to using the Poisson model.¹⁹ We estimate the model using university fixed-effect dummy variables and robust standard errors. This allows us to control for the unobserved institutional differences of universities (such as promotion rules, collaborative culture, emphasis on teaching), while the general error term structure allows for the errors to

¹⁸ A likelihood ratio test generates a test statistic that rejects the null hypothesis of no overdispersion, indicating a negative binomial regression model, which allows for overdispersion, is appropriate (Cameron and Trivedi 1998). The likelihood ratio test statistic is equal to 4916.05, which exceeds the 1% critical value of $5.41 = \chi_{0.98}^2(1)$.

¹⁹ In the NB2 model, the conditional variance is of the form $V[y_1|\mathbf{x}_1] = \mu + \alpha\mu^2$ which has the following density:

$$\Pr(y|\mu, \alpha) = \frac{\Gamma(y + \alpha^{-1})}{y! \Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu} \right)^{\alpha^{-1}} \left(\frac{\mu}{\alpha^{-1} + \mu} \right)^y$$

where $\Gamma()$ is the gamma function. Accordingly, we estimate the log likelihood function:

$$\begin{aligned} \ln L(\alpha, \beta) &= \sum_{i=1}^n \left\{ \sum_{j=0}^{y_i-1} \ln(j + \alpha^{-1}) - \ln y_i! - (y_i + \alpha^{-1}) \right. \\ &\quad \left. \times \ln(1 + \alpha \exp(\mathbf{x}_i'\boldsymbol{\beta})) + y_i \ln \alpha + y_i \mathbf{x}_i'\boldsymbol{\beta} \right\}. \end{aligned}$$

¹⁵ There has been a dramatic increase in the number of published authors in life science journals (over 11 million citations in PubMed/MEDLINE between 2000 and 2004 as compared to just 3 million between 1975 and 1979).

¹⁶ Leading journals report declining acceptance rates for submitted articles over the past several decades. For instance, the acceptance rate of Nature decreased by nearly a third in the last decade from 11.5% in 1997–99 to 7.6% (2009–2011).

¹⁷ The authors own analysis from the data used in Foltz et al. (2011). For a description of the Foltz et al. relative citation methodology and data sources, please see Foltz et al. (2011).

Table 2. Main Results: Negative Binomial Regression

VARIABLES	(1) Journal Articles	(2) Output	VARIABLES	(1) Journal Articles	(2) Output
Research (%)	0.0267*** (0.00522)	0.0241*** (0.00504)	Years Since PhD	-0.0233** (0.00908)	-0.0191** (0.00865)
Research (%) ²	-0.000179*** (5.31e-05)	-0.000164*** (5.07e-05)	Years Since PhD ²	0.000192 (0.000208)	0.000171 (0.000196)
Research Pct* 1979	-0.0165* (0.00952)	-0.0231** (0.00948)	Grad Students	0.0654*** (0.00928)	0.0675*** (0.00903)
Research Pct* 1989	-.0139* (.00818)	-.0162** (.00733)	Post-Docs.	.170*** (.0249)	0.172*** (0.0236)
Research Pct* 1995	-.00467 (.00859)	-.00404 (.00819)	Extension Appt. (bin)	-.00168* (.000990)	-0.00101 (0.000915)
Research Pct ² * 1979	.000140* (8.44e-05)	.000187** (8.30e-05)	5 Year Budget	.0403*** (0.0130)	0.0344*** (0.0129)
Research Pct ² * 1989	0.000113 (7.42e-05)	0.000136** (6.76e-05)	Budget ²	-0.000120*** (3.85e-05)	-9.53e-05** (3.82e-05)
Research Pct ² * 1995	5.71e-05 (8.57e-05)	5.20e-05 (7.94e-05)	Tenure Status	0.311*** (0.0385)	0.328*** (0.0373)
Year 1979	.0659 (.253)	.264 (.256)	Gender	.105* (.0545)	.0816 (.0511)
Year 1989	.111 (.213)	.161 (.188)	Disc: Ani Sciences	.480*** (.125)	.479*** (.119)
Year 1995	-0.142 (0.202)	-0.135 (0.197)	Disc: Plant Sciences	.387*** (.122)	.441*** (.116)
Constant	0.715*** (0.270)	0.777*** (0.258)	Disc: Env. Sciences	.237* (.131)	.321*** (.122)
			Disc: Food Sciences	.565*** (.132)	.577*** (.125)
Observations	1,844	1,844			
Univ FEs	Yes	Yes			

Note: Robust standard errors in parentheses *** $p < .01$, ** $p < .05$, * $p < .1$.

be correlated with other covariates, such as disciplines or years.²⁰

Average Factor and Labor Productivity

In order to test for differences in average factor and labor productivity over different time periods, we use time dummies and interact the labor allocation variable with time variables, allowing the marginal product of labor to vary across time periods. Our baseline estimation equation, which is structurally identical to equation (1), takes the form:

$$\begin{aligned}
 (2) \quad \ln(Y_i) = & \phi + \theta T_t + \gamma_{1a} L_i + \gamma_{1b} L_i^2 \\
 & + \gamma_{2a} (L_i * T_t) + \gamma_{2b} (L_i^2 * T_t) \\
 & + \mathbf{X}'\boldsymbol{\beta} + \mathbf{Z}'\boldsymbol{\delta} + \eta_j + \epsilon_{ij}
 \end{aligned}$$

²⁰ Our results are robust to using other standard error structures such as clustering and omitting the university fixed effects.

where T_t is a time trend, L_i is the actual allocation of time to research, and $(\eta_j + \epsilon_{ij})$ is a two part error term including both university fixed effects, η_j and a standard error term. $\mathbf{X}$ represents a vector of other inputs including the number of graduate students and post-docs working in the lab or on the faculty member's research team as well as the average annual research budget and budget-squared. Finally, $\mathbf{Z}$ is a vector of control variables including demographic characteristics of the faculty member; namely, years since Ph.D., years since Ph.D.-squared, a faculty gender dummy variable, and tenure status. The vector $\mathbf{Z}$ also includes four disciplinary dummy variables to account for field differences in journal publication. Appendix table 3 describes each of these variables. To measure average factor productivity, θ , the coefficient on time is estimated using year dummies to measure the change between earlier years and 2005. For labor productivity, γ_{2a} and γ_{2b} are the parameters that test for the

Table 3. Top-Ten vs. Non-Top Ten

VARIABLES	(1) Top-ten Journal Articles	(2) Non Top-ten Journal Articles
Research (%)	.0314*** (.0101)	.0250*** (.00546)
Research (%) ²	-.000234** (.000101)	-.000162*** (5.55e-05)
Research Pct* 1979	-.0102 (.0145)	-.0205* (.0114)
Research Pct* 1989	-.00412 (.0174)	-.0216** (.00855)
Research Pct* 1995	.00164 (.0170)	-.00711 (.00969)
Research Pct ^{2*} 1979	.000116 (.000136)	.000160 (9.96e-05)
Research Pct ^{2*} 1989	6.64e-05 (.000158)	.000159** (7.69e-05)
Research Pct ^{2*} 1995	-1.60e-05 (.000174)	8.00e-05 (9.38e-05)
Constant	.689* (.397)	.764*** (.277)
Observations	603	1,241
Univ FEs	Yes	Yes
Input and Control Vars.	Yes	Yes
Year Dummies	Yes	Yes

Note: Robust standard errors in parentheses *** $p < .01$, ** $p < .05$, * $p < .1$. Input variables are: Graduate students, Post Docs, Budget, Budget². Control Variables include: Gender, Years since PhD, Years since PhD², Tenure Status, Extension Appointment (%), Dummies for Animal Sciences, Plant Sciences, Food Sciences, and Environmental Sciences.

change in the effect of faculty research time allocation on article output across the four time periods. We expect that $\gamma_{1a} > 0$ since the proportion of time spent on research should positively affect output, but if there is an increase in output per unit time after controlling for other factors, then $\gamma_{2a} < 0$. Because of diminishing marginal returns, we predict the signs on the squared terms γ_{1b} and γ_{2b} should be the opposite of linear terms. We include terms that separately test the 1979, 1989, and 1995 research time slopes to estimate the productivity of faculty labor time, relative to 2005, the baseline year.

Panel Methods

In addition to the cross-sectional data collected in each of the surveys, the surveys contain panel data for the years 1995 and 2005, which allow us to track the evolution of time allocation and research output over these ten years for a consistent sample of

panel respondents. In order to estimate productivity effects in the faculty panel, we deploy a fixed-effects negative binomial econometric model.²¹ Under this specification, we assume that $Y_{it}|\mu_{it} \sim \text{Poisson}(\mu_{it})$, where $\mu_{it}|\alpha_{it} \sim \Gamma(\lambda_{it}, a_{it})$, and $\lambda_{it} = \exp(x_{it}B)$. As in the cross-section version, α_{it} is the dispersion parameter to be estimated except that α_{it} will be the same in both time periods for a given panel observation (Hausman, Hall, and Griliches 1984). The panel specification is estimated as a conditional log-likelihood function and follows equation (2):

$$(3) \quad \ln(Y_{it}) = \phi + \theta T_t + \gamma_{1a}L_{it} + \gamma_{1b}L_{it}^2 + \gamma_{2a}(L_{it} * T_t) + \gamma_{2b}(L_{it}^2 * T_t) + \mathbf{X}'\beta + v_i + \epsilon_{it}.$$

In equation (3), neither individual characteristics ($\mathbf{Z}$) nor university fixed effects, η_j , enter the model. Instead, v_i , the individual fixed effects, capture both individual and university-specific characteristics. As in equation (2), the coefficients of interest are γ_{2a} and γ_{2b} .

Relative Prices

Across universities, an individual faculty's research, teaching, and grant raising efforts will likely vary with the value that her university places on each activity for evaluating salary, tenure, and promotion. In each of the four surveys, however, we have information on the incentives for tenure and promotion which guide faculty time allocation and output.²² Using these data, we create a measure of relative "reward" of these activities and use them to price inputs in the faculty's production function.²³ These relative prices provide a control measure for incentives that may have shifted faculty effort toward outputs other than public research and thereby

²¹ Results using the fixed-effects Poisson model, which makes weaker distributional assumptions, yields similar (and more statistically significant) results. The Poisson model also avoids the incidental parameters problem. The drawback of this model is that it does not allow for overdispersion of the independent variable.

²² The survey asks faculty to place a value between 1 and 5 on the "reward" associated with "many journal articles," "high-quality journal articles," "teaching evaluations," and so forth.

²³ Using the 2968 observations which report information on the reward to various activities, we create an index of relative prices for each year and university. In each university-year reward category, there are an average of 13 observations, with values ranging between zero and 60.

bias our results. Using the reward for “many” journal articles as the numeraire good, we create relative prices for faculty teaching, grant raising, and high-quality journal articles. For teaching, the adjusted measure is:

$$(4) \quad AdjTeaching_i = \frac{P_{teaching_{j,t}}}{P_{many_{j,t}}} * TeachingPct_i$$

where $p_{many_{j,t}}$ is the reward for “many” journal articles at university j in year t ; $p_{teaching_{j,t}}$ is the reward for teaching; and $TeachingPct$ is the actual percentage of time spent teaching for that faculty member. Using an adjusted measure for teaching and five-year budget, we modify equation (2) above and estimate the following equation:

$$(5) \quad \ln(Y_i) = \phi + \theta T_t + \gamma_{1a} L_i + \gamma_{1b} L_i^2 + \gamma_{2a} (L_i * T_t) + \gamma_{2b} (L_i^2 * T_t) + \mathbf{X}'\beta + \mathbf{Z}'\delta + \lambda_1 AdjTeaching_i + \lambda_2 AdjTeaching_i^2 + \lambda_3 AdjBudget_i + \lambda_4 AdjBudget_i^2 + \lambda_5 RelPrice_{high_{j,t}} + \eta_j + \epsilon_{ij}$$

where the adjusted measures are defined above and the $RelPrice_{high_{j,t}}$ term is the reward of high-quality journal articles divided by $p_{many_{j,t}}$, the reward for many journal articles.

Results

The baseline productivity estimations, reported in table 2, test average factor productivity (AFP) and labor productivity. The results provide no evidence for across-the-board changes in AFP; the coefficients on time dummies for 1979, 1989, and 1995 are small and not statistically significant. However, they do provide compelling evidence of rising faculty labor productivity after controlling for inputs and the fields and demographics of researchers. As expected, our measure of research time, research percentage, increases faculty output significantly in both journal articles and our measure of composite output, although at a declining

rate. The primary coefficients of interest—faculty research time interacted with time period intercepts—provide a measure of how labor productivity has changed over time. In column (1), using journal articles as the dependent variable, we find that there are significant differences in labor productivity between 1979, 1989, and 2005 as evidenced by the significant coefficient on the interaction between research percentage and the 1979 and 1989 dummies. Column (2) repeats this specification using the composite output variable and gives even stronger results than column (1) in terms of showing a progression of rising faculty productivity from 1979 to 2005.²⁴ We also find strong positive effects of increased research budget and more graduate students and post-docs.

Next, we test for differences in our estimates of AFP and labor productivity changes across top-ten and non-top-ten universities. With the sample split in this way, table 3 shows that the significant labor productivity increase in the full sample appears to be based on significant changes at non-top ten universities. At these universities, the coefficients on the switching terms are all negative and significant at the 5% level in 1979 and 1989, providing strong evidence of productivity growth in non-top ten schools from 1979 to 2005 and 1989 to 2005. Meanwhile the key coefficients on research productivity in column (1) are not significant for the top-ten universities, although their signs are primarily in the same direction. As found in the research on BITNET’s effect on universities (Agrawal and Goldfarb 2008; Ding et al. 2009) and Foltz et al.’s (2011) aggregate productivity work, the non-top ten Land Grant universities appear to be the ones that gained the most in terms of research productivity after the revolution in computation and improvements in the suite of life-science technologies available to researchers. These split sample results underscore the potential heterogeneity of research processes across Land Grant universities, as well as a potentially equalizing effect of new technologies in agriculture and life sciences.

Overall, the cross-section data results provide strong evidence for a temporal trend

²⁴ In the regressions that follow, we use journal articles rather than the composite output measure as the dependent variable. The results using the composite measure, available from the authors, are equally strong and provide the same inference.

Table 4. Panel Data Results

VARIABLES	(1) Cross-section Journal articles	(2) Cross-section Journal articles	(3) Panel data Fixed effects Journal articles	(4) Panel data Fixed effects Journal articles
Research (%)	.0277*** (.00466)		.0296*** (.00943)	
Research (%) ²	−.000189*** (4.73e−05)		−.000265*** (9.76e−05)	
Research Pct* 1995	−.00702 (.00859)		−.0324** (.0139)	
Research Pct ² * 1995	8.31e−05 (8.60e−05)		.000315** (.000126)	
Doing Research (%)		.0246*** (.00545)		.0272*** (.00937)
Doing Research ²		−.000256*** (7.43e−05)		−.000360*** (.000139)
Doing Research*1995		−.0188** (.00836)		−.0215* (.0121)
Doing Research*1995 ²		.000231** (.000105)		.000272* (.000147)
Constant	.550** (.241)	1.083*** (.283)	3.004*** (.776)	3.658*** (.974)
Observations	735	717	294	292
Groups			147	146
University Fixed Effects	Yes	Yes	No	No
Year Dummies	Yes	Yes	Yes	Yes
Input/Control Variables	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses *** $p < .01$, ** $p < .05$, * $p < .1$. Input variables are: Graduate students, Post Docs, Budget, Budget². Control Variables include: Gender, Years since PhD, Years since PhD², Tenure Status, Extension Appointment (%).

of higher labor productivity associated with declining research time for faculty in part due to more time spent on grant administration or competition. Using an analysis of factor change in 2005, we find that a one unit increase in research time percentage would increase productivity by 2.9%. If researchers were able to dedicate just 5% more of their time to research, the model predicts journal output would increase by 1.69 articles over each five-year period. While faculty labor is important, it is worth noting that other inputs matter as well. We find that the marginal effect of an additional graduate student raises expected output by 6.4% and a post-doc by 22.6%, holding all other variables constant.

Panel Results

The cross-sectional results could be subject to the criticism that it is unobserved or unobservable faculty characteristics that drive the observed productivity increases.

If, for instance, faculties in 2005 are intrinsically more able or better trained than in past years, this could account for the observed productivity change. The panel data estimates in table 4, by following the same faculty members over a ten-year period, account for any unobservable time-invariant biases or changes in sample makeup that might exist in the cross section. For comparison purposes, columns (1) and (2) of table 4 show the results from the random-sample cross-sectional data from just 1995 and 2005, while columns (3) and (4) show the results of the fixed effects negative binomial using the panel, which contains information on 147 faculty in 1995 and 2005. The columns use, respectively, the “Research Percentage” and “Doing Research” variables to measure faculty labor input and have the standard set of control variables. The consistency in the parameter estimates between the panel and cross-section is remarkable: for example, the estimated parameters on the labor variables, “Research Percentage” and “Doing Research” and their squares, are the same to

Table 5. Relative Prices

VARIABLES	(1)	(2)	(3)	(4)
	Relative Prices		Teaching <15% Journal Articles	Teaching 15% Journal Articles
Research (%)	.0274*** (.00532)	.0234*** (.00517)	.0298*** (.00720)	.0363*** (.00847)
Research (%) ²	-.000210*** (5.54e-05)	-.000174*** (5.34e-05)	-.000206*** (7.08e-05)	-.000315*** (8.93e-05)
Research Pct* 1979	-.0184* (.00942)	-.0251*** (.00943)	-.0307** (.0150)	-.0190 (.0121)
Research Pct* 1989	-.0147* (.00801)	-.0167** (.00721)	-.0306*** (.0102)	-.0208 (.0140)
Research Pct* 1995	-.00930 (.00883)	-.00729 (.00830)	-.0114 (.0120)	-.0226 (.0142)
Adj. Teaching %	-.00335 (.00371)	.000975 (.00359)	.0314 (.0284)	-.00581 (.00633)
Adj. Teaching % ²	-4.76e-05 (5.27e-05)	-9.15e-05* (5.12e-05)	-0.00218 (0.00317)	1.29e-05 (7.77e-05)
Adjusted Budget (\$000)	.0363*** (.0135)	.0323** (.0135)	.0647** (.0257)	.0430*** (.0155)
Adjusted Budget ²	-.000106*** (3.91e-05)	-8.81e-05** (3.91e-05)	-.00206*** (0.000703)	-.000125*** (4.49e-05)
Rel. Price High-Quality Articles	-.0843 (.238)	-.171 (.226)	-.655 (.522)	.0148 (.250)
Constant	1.025*** (.366)	1.106*** (.344)	1.735** (.679)	.750 (.467)
Observations	1,844	1,844	492	1,352
Univ FEs	Yes	Yes	Yes	Yes
Input and Control Vars.	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses *** $p < .01$, ** $p < .05$, * $p < .1$. Input variables are: Graduate students, Post Docs, Budget, Budget². Control Variables include: Gender, Years since PhD, Years since PhD², Tenure Status, Extension Appointment (%), Dummies for Animal Sciences, Plant Sciences, Food Sciences, and Environmental Sciences.

three decimal places across the cross-section and panel data estimates.

When we consider the key variable of interest, the interaction of labor time with the 1995 dummy, the panel estimates show significantly lower levels of labor productivity in 1995 than in 2005. While the panel data show a more statistically significant effect for the research percentage than in the cross section, the doing research measure goes from significant at a 5% level to merely a 10% level in the panel data estimate. In the case of both the research percentage measure and the doing research measure, the net productivity of labor in 1995 is quite small while that of 2005 is significantly positive. Because we control for age and experience of the faculty in the panel through the variable “Years since Ph.D.” and its square, this implies that it is not lifecycle effects but rather improvements in labor productivity, which are driving the increase in productivity. Overall, these

panel data results provide strong evidence that the results in this work are not driven by changes in the cross-sectional sample or unobserved productivity improvements of faculty over the years; rather they show consistent evidence of labor productivity improvements.

Relative Prices

Table 5 depicts the results of our estimations using the relative price measures to capture how incentives for teaching and grants may have affected journal article output. These results include the adjusted measures of teaching percentage and five-year budget, with these variables normalized by their relative importance in the university, as well as a variable measuring the relative price of high-quality journal articles. If faculty are at a university where particular attention is paid to teaching, grantsmanship, or high-quality

Table 6. Robustness Checks (Budget Variable Variations)

VARIABLES	(1) Without Budget Journal Articles	(2) Budget Interaction Journal Articles
Research (%)	.0287*** (.00507)	.0261*** (.00530)
Research (%) ²	-.000195*** (5.13e-05)	-.000175*** (5.37e-05)
Research Pct* 1979	-.0194** (.00939)	-.0166* (.00954)
Research Pct* 1989	-.0174** (.00792)	-.0146* (.00820)
Research Pct* 1995	-.00809 (.00863)	-.00290 (.00867)
5 Year Budget		.0568** (.0228)
Budget ²		-.000168** (6.77e-05)
Budget*1979		-.00148 (.0402)
Budget*1989		-.00135 (.0283)
Budget*1995		-.0209 (.0526)
Constant	.718*** (.265)	.698** (.272)
Observations	1,893	1,844
Univ FEs	Yes	Yes
Input and Control Vars.	Yes	Yes
Year Dummies	Yes	Yes

Note: Robust standard errors in parentheses *** $p < .01$, ** $p < .05$, * $p < .1$. Input variables are: Graduate students, Post Docs, Budget, Budget². Control Variables include: Gender, Years since PhD, Years since PhD², Tenure Status, Extension Appointment (%), Dummies for Animal Sciences, Plant Sciences, Food Sciences, and Environmental Sciences.

articles, they might produce fewer articles.²⁵ Columns (1) and (2) show the results of this estimation using journal articles and composite output, respectively, as the dependent variable. As in our main result, there is a negative and significant coefficient on the 1979 and 1989 labor productivity terms. The amount of time spent teaching had an insignificant effect on the research output of faculty, using both journal articles and the composite measure.²⁶ Columns (3) and (4) split the sample into those faculty with teaching responsibilities above and below 15% of their total time, as a way of testing differences between primarily research faculty and others. As with the first two columns, there is no effect of teaching time allocation on

output. However, faculty with light teaching loads are affected by their university's focus on high-quality journal articles; among this subgroup, they produce slightly fewer articles. In addition, the increase in productivity for 2005 relative to 1979 and 1989 is higher in both magnitude and significance for this subgroup than for those with higher teaching loads.

Robustness Checks

The last two tables address potential concerns associated with the budget and with our dependent variable. Table 6 adds two robustness checks related to our measure of a faculty's budget. One concern is that we might induce multicollinearity by double counting the budget, since a large portion of research budgets are used for the salaries of faculty, graduate students, and post-docs, which are already accounted for in our regression. A separate concern is that the Huffman-Evenson deflator we use does

²⁵ Across all of the faculty members, producing many journal articles was rated higher (4.19/5) than producing high quality journal articles (3.59/5), but 15% of the respondents ranked high-quality journal articles as being more important.

²⁶ This same effect is robust to using raw teaching time percentages rather than the incentive adjusted value.

Table 7. Robustness Checks: Citation-adjusted articles (OLS with 2005 data only)

VARIABLES	(1)	(2)
	Web of Science: Ln(Journal Articles)	Web of Science: Ln(Quality-Adjusted Journal Articles)
Research (%)	.125*** (.0326)	.123*** (.0360)
Research (%) ²	-.000702** (.000299)	-.000565 (.000351)
Observations	710	710
R-squared	.289	.321
Univ FEs	Yes	Yes

Note: Estimation includes the same control variables as in table 2. Robust standard errors in parentheses *** $p < .01$, ** $p < .05$, * $p < .1$

not fully or adequately account for changes in laboratory machinery or computational power, which could bias the results. Column (1) of table 6 addresses the first concern by dropping the budget variable. These results have similar and significant negative coefficients on the switching terms, as compared to our main results. The second column includes six terms interacting the budget variable (and its square) with year dummies, to account for potential problems in our deflators. None of the coefficient on the interacted budget terms are statistically significant, and our main results hold here as well.

Finally, table 7, as best as we can with the available data, addresses concerns that our measure of output does not take into account the quality of the articles produced. Although we do not have information on citation rates for articles from the 1979, 1989, and 1995 surveys, we obtained publication and citation counts from the Web of Science for faculty respondents of the 2005 survey for journal articles produced between 2001 and 2005.²⁷ Using ordinary least squares (OLS) we regress the log of the average number of journal articles per year on the same explanatory variables used in our main specification, while the second column uses the log of quality-adjusted journal articles as the

dependent variable.²⁸ If normalizing by the number of citations had a substantial effect on the analysis, the results would show different coefficient estimates on research time. Instead, we cannot reject the null hypothesis that the coefficient estimates on our two variables of interest, research time and its square, are same between the number of journal articles and the quality-adjusted measure.²⁹ Thus we believe that any bias from quality differences is likely to be small.

Conclusion

Our main finding is that increases in faculty labor productivity supported stable public research output in an era of diminishing faculty time for research and increased incentives for commercially oriented, private, research. This result is a critical addition to the literature on university agricultural research, because it explicitly incorporates the issue of whether scientists are able to make time for science. We find direct evidence that faculty struggle to do so, but that they are also benefitting from an era of improved productivity associated with major breakthroughs in life science and informational technology and tools.

This analysis also demonstrates that productivity advances and rising administrative time demands on faculty cut in opposite directions in their effects on faculty research outputs. It appears that technological change produced a significant labor research productivity boost among agricultural and life sciences faculty at U.S. universities in the three decades leading up to 2005. Although our data do not allow for explicit modeling of how improved information technology or other scientific advances have affected faculty output, a potential approach would be to use university-level data sets to measure the spread of these technologies, such as in [Ding et al. \(2009\)](#). The estimates presented here of significant labor productivity changes are

²⁷ Faculty names were searched in the Web of Science database generating article counts and the number of times each of their articles had been cited. We dropped 76 respondents because their names could not be uniquely identified (e.g., John Smith). The correlation between the Web of Science and self-reported article counts was 0.823. Given that Web of Science omits lesser journals, it is not surprising that there is not a 100% correlation.

²⁸ Quality is adjusted by multiplying the scientist's journal article count by his citation count divided by the average number of citations per article within the faculty's discipline. In order to keep researchers with zero articles, a small number (.000001) was added to this variable before the log was taken.

²⁹ Test statistics of inequality of the coefficients, $\chi^2(1)$, ranged from 1.05 to .01, which were not significant at even a 25% confidence level, allowing us to accept the null hypothesis of coefficient equality.

likely an underestimate of the full productivity change, since they do not account for rising Land Grant university research quality and increasing alternate demands of commercialization and patenting. At the same time, increases in administrative workloads of faculty in both explicit and implicit forms, perhaps in part fostered by technological change (Acemoglu et al. 2007), have reduced faculty time allocation to research sufficiently to leave the core scholarly research activities at the same output level as before the productivity improvements. The evidence from these data suggests that the benefits of increased faculty productivity substantially have been swallowed by increases in administrative work and the search for competitive grants, rather than either generating new scientific output or freeing up faculty time to teach the next generation of scholars. This finding raises serious questions about whether the rising administrative demands on faculty time at U.S. universities from both declining support staff and increased administrative rules are reducing the benefits of the technological revolution in the life sciences and whether time allocation is optimal at U.S. Land Grant institutions. If time allocation were optimal, it would mean that the marginal value of faculty time allocated to administration had risen over time relative to the value of research efforts.³⁰

In summary, our empirical analysis reveals robust evidence that explains an apparent productivity paradox in research output produced by agricultural and life science faculty at U.S. Land Grant universities. On the one hand, improvements in faculty research productivity measured in terms of output per unit time increased significantly from 1979 to 2005, as much as 30%. On the other hand, those same faculty faced increasing demands on their time for a range of administrative tasks, some associated with research and others not. These findings raise important questions about whether universities should be encouraged and supported to find ways that would free up more time for faculty actually doing research. Given the high return to agricultural research activities and

public research output for U.S. agricultural production identified elsewhere, it would seem important to foster more faculty time for research. Most faculty members would be likely to respond enthusiastically to that type of organizational endeavor, especially if it were to come at the margin of administrative duties.

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³⁰ As suggested by a reviewer, such an increase in the marginal value of faculty time in administration could be the case if the time were necessary to secure large competitive grants, and it was those grants that allowed faculty labor productivity to increase. Our data do not, however, show that competitive grants have a significant effect on journal article productivity.

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Table A1. Universities included in the Sample

University		
Auburn	U. Alaska	U. Nebraska
Clemson	U. New Hampshire	U. Nevada
Colorado State	U. Arizona	U. North Carolina
Cornell	U. Arkansas	U. North Dakota
Iowa State	U. Connecticut	U. Rhode Island
Kansas State	U. Delaware	U. South Dakota
Louisiana State	U. Florida	U. Tennessee
Michigan State	U. Georgia	U. Vermont
Mississippi State	U. Hawaii	U. West Virginia
Montana State	U. Idaho	U. Wyoming
New Mexico State	U. Illinois	UC-Berkeley
Ohio State	U. Kentucky	UC-Davis
Oklahoma State	U. Maine	UC-Riverside
Oregon State	U. Maryland	Utah State
Penn. State	U. Massachusetts	UW-Madison
Purdue	U. Minnesota	Virginia Polytechnic
Rutgers	U. Missouri	Washington State
Texas A&M		

Table A2. Departments included in the sample

Discipline/Departments	Frequency	Percent
Animal Sciences		
Animal sciences, dairy sciences, meat and poultry sciences	350	18.98
Environmental Sciences		
Atmospheric science, environmental science, ecology, fisheries, hydrology, natural resources	1028	55.75
Food Sciences		
Food chemistry, food engineering, food sciences, nutrition	173	9.38
Plant Sciences		
Agronomy, biometry, biostatistics, crop sciences, entomology, geography, plant pathology, soil sciences	268	14.53
Total	1819	98.64

Table A3. Variable descriptions

Variable	Description
Journal Articles	The number of sole or co-authored journal articles in the five year period preceding the survey
Output	A composite research output variable calculated as follows: $\text{Output} = 1 * (\text{journal articles}) + 3 * (\text{books}) + .75 * (\text{book chapters}) + .5 * (\text{edited books})$
Research (%)	The percent of time allocated to research (additional options were: teaching, administration, extension and outreach, other)
Doing Research (%)	The percent of time allocated to research less time spent on administration or grant preparation
Years since PhD	The number of years since a faculty member completed his/her PhD
Grad Students	Respondents indicated the number of graduate students working “under their direction in their research program”
Post Docs	Respondents indicated the number of post-docs working “under their direction in their research program”
Extension Appt. (bin)	Binary variable equal to 1 if the faculty member had a formal extension appointment
Budget (5 year)	The average annual budget of a faculty member’s research program over the five years prior to the survey date. Data were converted into 2000 dollars using the Huffman-Evenson Agricultural R&D price index.
Tenure Status	Position of faculty member. 1 = Asst. Prof; 2 = Assoc. Prof; 3 = Full Prof.
Gender	Binary variable equal to 1 if the faculty is male
Animal Sci. (Disc.)	Binary variable equal to 1 if faculty is a member of an animal sciences department
Plant Sci. (Disc.)	Binary variable equal to 1 if faculty is a member of a plant sciences department
Env. Sci. (Disc.)	Binary variable equal to 1 if faculty is a member of an environmental sciences department
Food Sci. (Disc.)	Binary variable equal to 1 if faculty is a member of a food sciences department
Year	A dummy variable for each of the years 1979, 1989, and 1995. 2005 is the excluded year
Research Pct *(Year)	Interaction between the research percentage and the year dummy variable