Empirical Estimation of University Knowledge Production Functions for Knowledge Outputs Disseminated via Multiple Channesl

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Abstract:
Multiple types of knowledge outputs, associated with different spillover mechanisms, can result from the universities' knowledge production processes. Using a knowledge production function (KPF) framework, this study develops a simple taxonomy of the different types of knowledge outputs of the university—including knowledge disseminated via publications, via industry collaboration, and via formal technology transfer mechanisms. We compile a uniquely detailed institutional dataset at the level of academic departments and obtain robust estimates of year-to-year and long-run relationships between research inputs and each of these different types of knowledge outputs. We find that productivity varies: production of knowledge disseminated by publication and by direct collaboration with industry exhibits decreasing returns to scale, while production of knowledge disseminated by formal technology transfer appears to exhibit increasing returns to scale.

Keywords:
university research; knowledge production function; polynomial distributed lags; knowledge spillovers; public-private research collaboration; technology transfer

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1. Introduction

It is widely acknowledged that the creation of new knowledge is an important factor behind productivity gains and long-run economic growth (Romer, 1986, 1990; Lucas, 1988). And, since knowledge exhibits many of the characteristics of public goods or positive externalities, it is generally presumed that private economic activity underinvests in its creation (following Nelson, 1959, and Arrow, 1962), thus providing the basic policy rationale for public support of research at universities (Jencks and Riesman 1968; Nelson 1986; Cowan 2005). Today's research universities articulate three interwoven missions of education, research, and outreach. While the educational mission of the university focuses on imparting knowledge and skills to students—enhancing their future incomes as well as labor productivity for their future employers—the research and outreach missions of the university, respectively, focus on producing new knowledge and facilitating spillovers of that knowledge, particularly to stakeholders in industry (Stokes, 1997; Etzkowitz, 2003). University research has long served as a source of ideas for industrial innovation, spurring the development of new products and processes, and driving regional economic development (Jaffe, 1989; Mansfield, 1991, 1995; Rosenberg and Nelson 1994; Audretsch and Feldman, 1996). In the United States, in 2013, university research accounted for $64.7 billion, or 14 percent, of the total $456 billion of R&D performed in the U.S. economy, and, within that, universities accounted for 51 percent of the basic research performed. Moreover, almost 95 percent of the funding for research performed at U.S. universities came from public or non-profit sources; only 5.4 percent came from business (NSF, 2016). In the European Union, in the same year, higher education research and development (HERD) accounted for €66 billion, or nearly 23 percent of total R&D performed within the EU economy (EuroStat, 2015).

In the final decades of the 20th century, the rise of the "knowledge economy" (Romer, 1990; Mokyr, 2002; Kahin and Foray, 2006) was characterized by a pervasive shift toward greater utilization of intellectual capital in economic processes of value creation, combined with vastly greater ease of publication, storage, search, and retrieval of information due to development of the Internet (Powell and Snellman 2004). As knowledge itself has become more valuable, it has also become more contested, affecting university knowledge creation and dissemination activities in several regards (Slaughter and Leslie 1998; Geiger 2004; Winickoff, 2014). This has exacerbated policy debates over allocation of public resources to university R&D (Geuna et al, 2001), governance of research processes (Dagupta & David, 1994), and policies for how newly created knowledge is controlled and disseminated (Eisenberg and Nelson, 2002; Graff, Heiman, & Zilberman 2002; OECD 2003; Mowery et al 2004; Sampat 2006; NRC 2010).

These policy debates persist, to a certain extent, because of challenges in empirically measuring the full range of knowledge production and dissemination activities that go on at the contemporary research university. One major shortcoming in this regard is not unique to universities: R&D processes are often measured by accounting for inputs, such as research expenditures or numbers of scientists and engineers employed. Such measures, cannot, however, indicate how productive R&D processes are in generating knowledge outputs, the value of those outputs, or the mechanisms whereby those outputs impact the economy. Even among studies that do seek to model the relationship between the inputs and outputs of university research, many consider just a single type or single measure of knowledge output. The most common output measure is the count of new publications, sometimes in combination with the count of citations made to those publications. In addition, a number of studies utilize an output measure of patents, as patent licensing represents a newer, more controversial channel of knowledge dissemination from universities. Other research outputs arise or are transmitted via personnel exchange, collaborative research, extension services, consulting activities, and other similar “high-touch” channels wherein they may be more difficult to measure (Cote & Cote 1993; Cohen et al 1998; Agrawal & Henderson, 2002). However, ideally, systematic empirical analysis of university research productivity and impacts should include measures of all significant inputs and outputs of the knowledge production process.

An additional set of challenges faced by empirical studies of university research is related to the level of analysis, which is often dictated by the fact that data is often only available at an institutional or at an even more aggregated state or national level. Yet, arguably, the locus of much of the salient decision making and economic behavior that drives knowledge production at the university occurs at more disaggregated levels such as within colleges, institutes, centers, academic departments, or even within individual research groups (Etzkowitz, 2003).

In this study, we follow trends of the last decade for combining multiple large institutional datasets created, housed, and serving different purposes in different parts of an organization[4]. We compile from multiple sources across our home institution a uniquely detailed panel data set of research inputs and outputs, spanning more than twenty years, for each of the university’s 54 academic departments or similar research units. We build upon previous studies to estimate, at the departmental level, the knowledge production function, in order to explore several interrelated research questions: To what extent do different types of knowledge outputs, associated with different spillover mechanisms, result from the university’s knowledge production processes? Is there a systematic relationship over time between changes in R&D inputs and changes in the different types of research outputs? To what extent are economies of scale or scope evidenced in

[4] See, for example, “A Different Game: Special Report on Managing Information,” *The Economist*, Feb 25th 2010.

university knowledge production? And what implications do these relationships have for policies governing university research and knowledge dissemination?

2. Literature Review

2.1. Knowledge Production within Research Universities: Theory and Empirical Analyses

Our understanding of university research processes is rooted in the framework of knowledge production, treating new knowledge as if it were the output of a typical production process. The knowledge production function (KPF) was developed by Griliches (1979) and Pakes and Griliches (1980, 1984) to analyze the creation of patented inventions, considered to be useful indicators of otherwise unobservable increments of economically valuable new knowledge resulting from the R&D activities of 121 U.S. firms over 13 years. They find that by including several years of past research expenditures they are able to improve the fit of the patent production equation. However, they find the positive relationship between the input of research expenditures and the output of patents to holds only in the long-run: they do not find significant short-run effects in the lagged variable estimates. This may be due to data problems, such as truncation of the panel, or to misspecification of the lag structure, having placed no *a priori* restrictions on the relevant range of lags.

In one of the earliest applications of the KPF framework to university research, Pardey (1989) analyzes the input-output relationship in the agricultural research programs of 48 major state Land Grant universities in the U.S. over 13 years. Similar to Pakes and Griliches, he finds a significant positive long-run relationship between research expenditures and publications, yet, likewise, fails to find evidence of systematic short-run or point-to-point influence between particular lagged years' research expenditures and subsequent publications at the institutional level.

Adams and Griliches (1998) explore the research performance and productivity of 109 U.S. universities over 13 years. Their analysis finds that, at the aggregate level, research outputs such as publications exhibit constant returns to scale, but, at the institutional level, appear to exhibit diminishing returns to scale, although they acknowledge that this could be attributed to a number of measurement problems. Similar to Pardey (1989), they do not find any reliable systematic short-run relationship between changes in research expenditure inputs and changes in knowledge outputs.

Crespi and Geuna (2008) estimate the aggregate university KPF at a national level, utilizing a dataset of higher education R&D (HERD) for 14 OECD countries over 12 years. They develop a polynomial distributed lag (PDL) model of the relationship between research expenditure inputs and knowledge outputs over time. Yet, like the previous studies, they fail to find a systematic relationship between specific lagged years' inputs and outputs, and likewise they suggest that this may be due to the quality or level of aggregation of the data.

An alternative approach to the study of knowledge production considers the cost minimization function (CMF), based on the work of Baumol et al (1988) on multi-product industries and adapted by Cohn et al (1989) and de Groot et al (1991) to consider the economies of scale and scope of the multi-product "outputs" of universities. Following this approach, Foltz et al (2007; 2012) estimate a knowledge CMF for the joint production of three different university research output measures—publications, patents, and doctorate degrees—within the life sciences disciplines at 90 major U.S. research universities from 1981 to 1998. They find evidence of economies of scope between patents and the other two outputs, when quality adjusted. These effects appear to be more pronounced among the public Land Grant universities. They also find significant productivity growth over time, particularly among top tier universities. Factors that affect knowledge co-products include total research funding, the presence and experience of technology transfer offices, numbers of post-doc researchers, and the type of research funding, with evidence that federal funding and industry funding are complementary rather than substitute inputs. In particular, the consideration of multiple co-products enabled by the CMF approach is compelling, albeit again limited by data availability and level of aggregation.

While a number of studies extend and develop the KPF in the context of firm R&D (following Hall, Griliches, & Hausman, 1986), others apply the KPF in estimating regional-scale effects of aggregate university research (following Jaffe, 1989, Anselin Varga, Acs, 1997, and others). Few other studies have attempted to apply the KPF or CMF to model the production of discrete university research outputs directly. All of the studies we review that have done so appear to encounter similar challenges in measuring knowledge outputs, in model specification of the input-output lag structure, and in the level of analysis due to data aggregation.

2.2. Different Types of Knowledge Outputs

Knowledge is notoriously difficult to quantify. Many different indicators have been proposed and used to measure additions to the stock of economically useful knowledge, both in general and in particular, from universities. While knowledge itself is widely characterized in economic discourse as a pure public good, it has been argued that—at least in the act of transmission or "spilling over"—knowledge can deviate from Samuelson's (1954) classic description of being non-excludable and non-rival. Following Romer's (1990) conception of technology as more of a quasi-public good, being at least partially excludible, we propose a simple typology of knowledge outputs, based upon varying degrees of rivalry and exclusion to which an increment of new knowledge may be subject—whether that variation be due to intrinsic characteristics of the knowledge itself, to how it is handled legally or strategically, or to the size, nature, and number of firms that make up the potential users of that knowledge. Several broad types of knowledge outputs can be identified, thus, *according to the general pathway or spillover mechanism by which each is disseminated from its creator to subsequent users* (Fig. 1). (For suggestive analyses see Bekkers and Bodas Freitas, 2008, or DeFuentes and Dutrenit, 2012.) Each of these types of knowledge output has been reported and investigated in the literature as a direct product of university research.

	non-rivalrous (more codified, disembodied; lower absorptive capacity requirements; lower transaction costs; "slippery")	**more rivalrous** (more tacit, embodied; higher absorptive capacity requirements; higher transaction costs; "sticky")
non-excludable	I. Public domain (publications; citations)	II. Collaboration (public-private research projects; industry funding of university research; co-authorship; regional impacts/productivity changes)
more excludable	III. IPRs and licensing (invention disclosures; patents; licenses; patent citations)	IV. Venture creation (startups formed)

Fig. 1. A typology of knowledge outputs, according to the varying public-good attributes of that knowledge, and therefore characterized by the pathways or spillover mechanisms by which the knowledge outputs of each type tend to be disseminated, with common metrics for each type.

2.2.1. Public domain

As illustrated in Fig. 1, release via the public domain is understood to be the primary mechanism for dissemination of outputs of research that exhibit the strongest degrees of the public-good attributes of non-excludability and non-rivalry. Publications represent discrete and often incremental contributions to human knowledge, as well as acts of public disclosure and codified dissemination of that knowledge. While the knowledge contents of publications largely represent deposits into the public domain, it must be noted that, in legal terms, the actual scope of public availability to use published knowledge depends upon the extent to which that knowledge is not otherwise encumbered by intellectual property claims (Boyle, 2003).

Bibliometric studies have long exploited publications and citations data (classics include Garfield et al, 1964; de Solla Price, 1965; Narin, 1976). A number of econometric studies have used counts of publications, as well as counts of citations to those publications, as measures of the output of university research (Pardey 1989; Adams and Griliches, 1998; Crespi and Geuna, 2008; Adams and Clemmons, 2011). Others have also counted closely-related metrics, such as PhD dissertations or graduate degrees awarded (Adams & Griliches, 1998; Folz et al, 2012).

2.2.2. Collaboration

We identify the collaboration mechanism of knowledge dissemination as most appropriate for knowledge outputs that exhibit stronger "common-goods" characteristics, i.e. that are relatively non-excludable and, yet, are more rivalrous in transmission, either due to the more tacit or "sticky" nature of the knowledge, involving skills or routines, or due to higher absorptive capacity requirements for learning or using that knowledge after it is created. Such knowledge requires inter-personal interaction—such as coaching, apprenticeship, or collaboration in the R&D activities—and involves higher transaction costs to effectively spill over.

A number of surveys have reported on collaboration activities, from samples of university and industry respondents (Blumenthal et al, 1986; Cote & Cote, 1993; Landry, Traore, and Godin, 1996; Cohen, et al, 1998, 2002; Laursen & Salter, 2004; Link, Siegel and Bozeman, 2007). But it has proven difficult to directly measure collaborative activities in a systematic way across entire academic institutions or national systems over multiple years, due to the uncodified nature of the knowledge outputs as well as the multifaceted and often informal or private nature of the contacts involved. Therefore, it has been common practice to employ R&D input or process variables, which are more consistently reported, as proxies for the production and dissemination of such knowledge outputs. These proxies include counts of discrete public-private research projects or joint ventures, such as industry-university research centers (IURCs) or private participation in federally funded research and development centers (FFRDCs) (Carayol, 2003; Hall, Link, and Scott, 2003) and private-sector funding of university research (Geiger, 2012). One output-related proxy that has been systematically investigated is the occurrence of university-industry co-authorship on published scientific articles (Godin and Gingras, 2000; Zucker, Darby & Armstrong, 2002; Clark, 2011). Others have sought to measure such knowledge outputs indirectly. Assuming that such spillovers of tacit or uncodified research outputs are spatially circumscribed, a number of studies measure changes in industry R&D, industry locate decisions, or industry productivity as a function of regionally proximate university research (Jaffe, 1989; Audretsch and Feldman, 1994; Varga, 1998; Alston et al, 2010).

2.2.3. IPRs and licensing

Since the passage of the Bayh-Dole Act in the U.S. in 1980 and similar policies in many European countries, Japan, China, and elsewhere, use of intellectual property rights (IPRs) in the commercialization of university knowledge has been increasingly emphasized as a mechanism of knowledge dissemination and economic impact. The IPR/licensing mechanism is best suited when a greater degree of excludability is necessary in order to create incentives for investment in the follow-on development of an otherwise non-excludable and non-rivalrous knowledge output—essentially to solve a free-rider dilemma—by effectively imbuing the university knowledge output with greater private-good (when exclusively licensed) or at least club-good (when non-exclusively licensed) characteristics.

University invention disclosures, patents, and licensing agreements, as well as citations to university patents, have received considerable attention and empirical analysis (Jaffe, Trajtenberg, and Henderson, 1993; Henderson, Jaffe, and Trajtenberg, 1998; Jensen and Thursby, 2001;

Mowery, Nelson, and Sampat, 2001; Colyvas, 2002; Graff, Heiman, and Zilberman, 2002; Coupe, 2003; Geuna and Nesta, 2006; Stephan et al, 2007; Thursby, Fuller, and Thursby, 2009; Feller and Feldman, 2010). IPR-mediated technology-transfer activities, when compared with the other knowledge dissemination channels of the university, are still relatively minor (Cohen et al, 2002; Agrawal & Henderson 2002), yet it is likely to continue as a viable mechanism of managing knowledge outputs, while generating limited revenues for the university.

2.2.4. Venture creation

Finally, the venture creation mechanism works by raising private investments in the further development and dissemination of university knowledge via a startup firm, founded external to the university, where IPRs or secrecy makes the knowledge relatively excludable, and intrinsic tacitness, complexity, or context-dependence makes the knowledge relatively rivalrous in transmission. While this mechanism involves both IPRs and collaborative activities, it does not use them to facilitate direct dissemination of new university-produced knowledge to existing firms in industry. Rather, it uses them—in combination with other entrepreneurial activities—to create new entrants that may compete against established incumbents or, at a minimum, that may serve to "de-risk" early stage technologies to then be acquired by incumbent firms once proven commercially viable. A number of studies have developed metrics ranging from simple counts of startup companies, to measures of the success or economic impact of university startups (Franklin, Wright, and Lockett, 2001; Di Gregorio and Shane, 2003; Shane, 2004; O'Shea et al, 2005; Zhang, 2009; Rasmussen and Borch, 2010; Fini et al, 2011; Lundqvist, 2014; Rasmussen et al, 2014).

2.2.5. Measuring multiple university knowledge outputs

In addition to the aforementioned studies that focus on a single type of university research output, a number of empirical studies consider multiple knowledge outputs of the university.

Foremost among these are surveys that ask samples of respondents to identify and/or rank various ways by which knowledge spillovers from universities impact industry, including all four of the broad types of outputs laid out in Fig. 1 (see Blumenthal et al, 1986; Cote & Cote, 1993; Landry, Traore, and Godin, 1996; Meyer-Krahmer and Schmoch, 1998; Cohen et al, 2002; Laursen & Salter, 2004; De Fuentes and Dutrenit, 2012). Other studies explicitly model or measure interactions between two or more quantified outputs, with many focusing on questions specifically regarding tradeoffs between publications and patents. Agrawal and Henderson (2002) count the publications and the patents generated by individual researchers in two academic departments at MIT over 15 years. They find that researchers' numbers of patents are not related to their number of papers, but they are positively correlated with the number of citations to their papers, interpreting this to suggest that patenting may be complementary to more fundamental (i.e. highly cited) research. Payne and Siow (2003) estimate the effects of federal research funding on the output of both papers and patents at 68 U.S. research universities over 28 years, showing that the level of federal research funding positively affects the output of both, but does not significantly increase their quality as indicated by citations to both. Huang and Murray (2009) analyze the dynamics that arise when new knowledge regarding human genes and their functions are disseminated via both public domain and IPR mechanisms. They estimate that the granting of a of a patent involving a human gene has a slightly negative impact (of 0% to -3%) on the rate by which a corresponding academic publication on that same human gene subsequently receives citations. Thursby and Thursby (2011) analyze science and engineering faculty at 11 major U.S. research universities over 17 years, finding that successful patent licensing by a faculty member increases the subsequent volume of that individual's publications, as well as citations. Bonaccorsi, Daraio, and Simar (2006) find that, for 45 Italian universities over 5 years, increased industry research funding (indicating research outputs disseminated via collaborative channels) is associated with increased rates of publication. Collectively, results in the literature based on knowledge metrics suggest that the multiple types of research outputs of universities appear to be co-products of a common underlying knowledge production processes and their production generally exhibits economies of scope.

3. Data and Methodology

3.1. Data Descriptions

For this analysis, data on research inputs and outputs were collected from a variety of institutional sources across Colorado State University, the public Land Grant university for the state of Colorado. All data for this analysis were denominated at the smallest common accounting unit available, that of the 54 academic departments or analogous research units (e.g. institutes, centers, etc.) over 24 years, from 1989 to 2012. The research input data consist of two categories, representing financial inputs (research expenditures) and human capital (research FTEs). Data on physical capital—including laboratory space and durable research equipment—were also collected and tested in preliminary regressions but were not found to be significant determinants of knowledge production, at least on the margin, and were therefore omitted from subsequent analysis. The research output data were categorized according to the main mechanisms or channels of dissemination upon which they depend: (I) knowledge outputs disseminated via the mechanism of publication and release into the public domain; (II) knowledge outputs disseminated via direct collaboration with industry users of that knowledge; (III) knowledge outputs disseminated via the mechanism of formal intellectual property rights and licensing contracts; or (IV) knowledge outputs disseminated via the creation of startup ventures. In fact, a given research project may produce knowledge outputs that show up in two or more of these categories, arguably representing different aspects or dimensions of the knowledge arising from that line of research work. For practical purposes, the latter two types of knowledge outputs, while conceptually distinct, are combined in our analysis into a combined technology transfer metric (see below), due both to the empirical issue of the small numbers (or, conversely, the preponderance of zero values) observed but also to the institutional arrangement whereby they are jointly managed by the university's office of technology transfer. Table 1 provides summary statistics of all research input and output variables for the 54 departments and research units of the university from 1989 to 2012, resulting in a panel that is comparable in number of observations to those estimated in prior studies (Pakes and Griliches, 1980; Pardey 1989; Adams and Griliches, 1998; Crespi and Geuna; 2008).

Table 1
Summary statistics of all research input and output variables at the department or research unit level within Colorado State University, 1989-2012

	Mean	Std. Dev.	Min	Max	Sum	Group	Obs.
Research inputs							
Research expenditures (million $)	2.74	4.57	0	37.9	3,545.8	54	1,296
Full-time equivalent researchers (FTEs)	56.78	46.10	0	282.4	73,592.0	54	1,296
Research output measures							
Published journal articles (counts)	28.57	35.91	0	252.0	37,029.0	54	1,296
Industry co-authored articles (counts)	2.22	4.96	0	58.0	2,872.0	54	1,296
Private sponsor grant awards (million $)	0.18	0.52	0	5.4	230.3	54	1,296
Extension budget (million $)	0.08	0.21	0	1.3	105.7	54	1,296
Invention disclosures (counts)	1.13	2.99	0	28.0	1,470.0	54	1,296
Patent applications and grants (counts)	0.12	0.52	0	9.0	160.0	54	1,296
Startup companies (counts)	0.03	0.19	0	3.0	40.0	54	1,296
Research output index variables							
Combined collaboration metrics (counts)	5.50	12.02	0	167.0	7,131.0	54	1,296
Combined tech transfer metrics (counts)	1.29	3.37	0	29.0	1,670.0	54	1,296

Note: The results of ADF unit root tests indicate that all input and output variables have a stationary process at a 1 percent level of statistical significance by four different methodologies, such as inverse chi-squared, inverse normal, inverse logit *t*, and modified inverse chi-squared (except extension budget, which has a stationary process at a 5 percent level with only inverse normal and inverse logit t methodologies).

3.1.1. Knowledge Inputs

Annual Research Expenditures are reported by two different sources within the university, for different sets of years and at different levels of aggregation. First, departmental-level accounting data of annual research expenditures is available for the 54 individual departments and research units from 2007 to 2012. Second, the university's annual total research expenditures are available for the entire time period of the study, from 1989 to 2012. In order to generate a complete series at the department level, average expenditure shares by department over the available years of 2007-2012 are used to estimate or "backcast" research expenditure values as a share of the university total for all departments during the years of 1989-2006.[5] While not ideal, this method of imputing missing departmental values of this key input allows us to test for longer lag times in the KPF. Departmental shares of total university research expenditures over the observed years were quite stable, and discussions with research administration officials of the university confirm that they had been similarly stable in previous years. Total research expenditures for the university over the 23 year time period of the study was $3.5 billion. Annual research expenditures had exceeded $300 million by the final years of the study period.

Full-time equivalent (FTE) research appointments consist of the research share of professors' appointments, as well as non-tenured research staff, postdoctoral fellows, and graduate research assistants (GRAs). Data on university research FTEs is reported for the 54 departments and research units from 2003 to 2012.[6] Departmental values for prior years, from 1989 to 2002 were similarly calculated by "backcasting" average departmental shares of the reported total university

[5] The university switched accounting software systems in 2006, at which point prior years' departmental level data were archived and not carried forward into the new system. Accessing the values would have required perhaps hundreds of hours of university administrative staff time.
[6] Data from the Office of Institutional Research at CSU.

research FTEs for those years.[7] Annual count of research FTEs had exceeded 4000 by the final years of the study period.

3.1.2. Knowledge outputs disseminated via the public domain

Published academic articles: The primary measure of university research output are annual counts of research publications with at least one author affiliated with CSU, from 1989 to 2012, identified by departmental affiliation of the CSU author(s).[8] The total count of publications for this time period is 37,029. The data for each publication includes author names and institutional affiliations. A sizable fraction of the raw publications data reports authors' departmental affiliation. By standardizing names of all authors affiliated with CSU, departmental affiliation could be imputed from those records where it was reported to other records where it was not. For those identified CSU authors for which departmental affiliation was missing in the data altogether, the information was obtained by hand from secondary sources, such as departmental web pages. In those cases with co-authors from two or more departments, the article was counted once for each department represented. On average, each department produced 28.57 publications annually. As a result, all 37,029 CSU publications were attributed to at least one department within the university. Rate of research publications had come to exceeded 2,000 per year by the final years of the study period.

3.1.3. Knowledge outputs disseminated via university-industry collaboration

Published academic articles with industry co-authors: Co-authorship between researchers at the university and collaborators in industry is considered a leading indicator of knowledge outputs disseminated via more interpersonal or collaborative channels. Publication of an article is, in itself,

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[7] Annual university total FTE data collected from various years of the CSU Fact Book.
[8] The records of CSU authored publications were collected from the Web of Knowledge (Thomson Reuters), accessed via CSU Libraries.

indication of knowledge output disseminated via the public domain; however, the fact that the research was conducted jointly with industry R&D personnel indicates that other knowledge co-products—such as tacit skills or unpublished data and technical findings of specific relevance to the industry partner—may have also been exchanged with them more directly or informally. In some instances a listed industry co-author is a graduate of the university, recently hired by industry, a commonly cited mechanism for interpersonally-mediated dissemination of tacit knowledge and skills from the university to industry. All of the 37,029 publications with a CSU author (see above) were additionally categorized according to the nature of co-authors' affiliations, including (i) all co-authors affiliated with CSU only, (ii) all co-authors affiliated with academic or public sector institutions only, or (iii) at least one co-author affiliated with a company or other private-sector organization. The total number of articles with an industry co-author was 2,872, or 7.8 percent of all publications during this time period. Annual counts of articles with industry co-authors were then tallied by department. When university authors from more than one department were involved on an industry co-authored article, it was counted, in the same manner as above, once for each department.

Departmental expenditures on Cooperative Extension: Given the university's role as the Land Grant university for the state of Colorado, Cooperative Extension activities involving tenure-track faculty and research staff with Extension-funded appointments, located within academic departments, represent another form of knowledge dissemination. Those with Extension appointments engage with private sector stakeholders throughout the state, communicating industry-relevant results from their own research as well as the research of their colleagues in the department. Our preliminary explorations found that departmental-level budget expenditures on Extension appointments and activities is perhaps the only variable systematically reported for all departments and years, related to the quantity of industry-oriented knowledge dissemination from the department via the mechanism of Cooperative Extension.[9] Extension budgets at the department level are in dollars per year from 2003 to 2012.[10] Total annual university Extension budgets were available for the earlier period from 1989 to 2002,[11] and therefore Extension expenditures for individual departments over these years were estimated using the "backcasting" method, based on observed departmental shares of the university totals from 2003-2012. Total departmental budget Cooperative Extension expenditures for the university, for these years, was $105.7 million.

Research grants and contracts from industry sponsors: Even though the financing of research via grants or contracts from industry are, technically speaking, an input to research, the extent of such awards to a department can be considered a proxy for the quantity of research being conducted with an industry orientation and from which knowledge outputs may be disseminated, at least in part, via contact and interactions between university researchers and those industry sponsors. Grant and contract awards data are available for the entire university from 1989 to 2012.[12] For each award we identified the funding source as a public-sector or a private-sector ("for profit" or industry) sponsor. Total value of private sector grant awards over this time period was $230.3 million, representing just 6.5 percent of the university's total research.

Combined Collaboration Metric: These three measures or proxies of knowledge output were found to be relatively uncorrelated across departments and years, and thus are assumed to be relatively independent. We therefore seek to combine them into a single knowledge output variable. To do so, first, we transform the dollar amount of expenditures on Cooperative Extension and the

[9] Other metrics of extension activity, such as contact hours, numbers of consultations, etc., were found not to be systematically collected or reported across all departments or all years.
[10] Departmental level data provided by the Agricultural Business Center of the College of Agricultural Sciences at CSU.
[11] University level data collected from the CSU Fact Books for the respective years.
[12] From the Contracts and Grants Database accessible online at the Office of the Vice President for Research, CSU.

dollar value of private-sector research grants into "publication equivalent" units, based on each department's ratio of total journal article publications to total research expenditure dollars in the same year. We then sum these "publication equivalents" of extension budgets and private sector grant awards with the counts of industry co-authored publications, denoting this linear combination as the *combined collaboration metric*[13], with one benefit of this measure being that it is roughly comparable to the measures of knowledge outputs disseminated via the other two channels.

3.1.4. Knowledge outputs disseminated via technology transfer mechanisms

Invention Disclosures: The first indicator of research results that have impact via the technology transfer mechanisms mediated by formal intellectual property and licensing contracts are inventions resulting from university research disclosed to the university's technology transfer office, from 1989 to 2012. During the time period of this study, CSU research led to 1,470 invention disclosures.[14]

Patent Applications and Issued Patents: Patent data provide a second indicator of knowledge outputs disseminated via technology transfer mechanisms, building directly upon invention disclosures. Patent data include patent applications and patents granted, characterized by inventor names and publication or issue dates. CSU inventors were identified and affiliated with a university

[13] $Coll_{i,t} = IA_{i,t} + PEExtension_{i,t} + PEPGrant_{i,t}$, where *IA* is industry co-authored articles, a subset of total publications, *PEExtension* is a "publication equivalent" measure of the extension budget, and *PEPGrant* is a "publication equivalent" measure of the value of private-sponsor grant awards for department *i* in time period *t*. $PEPGrant_{i,t} = (Tpubs_{i,t}/R_{i,t})\cdot PGrant_{i,t}$ and $PEExtension_{i,t} = (Tpubs_{i,t}/R_{i,t})\cdot Extension_{i,t}$, where *TPubs* is the total publication count and *R* is research expenditures. $Extension_{i,t}$ is the actual dollar value of the extension budget expenditures by the department *i* in year *t*, and $PGrant_{i,t}$ is the dollar value of private-sponsor grants and contracts awarded to department *i* in year *t*. Given that these latter proxies are financial data, this transforms them to units similar to count of articles, using average research expenditures per total publications for that department in that year, essentially converting these knowledge output proxies into the "currency" of research publications.

[14] Data provided by CSU Ventures, which serves as the technology transfer office, located within the external CSU Research Foundation, on behalf of the university.

department, providing annual counts of patent publications by department from 1990 to 2011. During this time CSU research led to 160 published patent applications or issued patents.[15]

Startup companies seeking to develop commercial applications of knowledge arising from university research are the main indicator of the venture creation mechanism of knowledge dissemination. Data on CSU startup companies is characterized by names of the companies, incorporation dates, names of individual founders, as well as and the academic department of the university-affiliated founders, from 1989 to 2012. During this time CSU research led to 41 startup companies.[16]

Combined Technology Transfer Metric[17]: Due to low numbers of any one of these measures, we combine counts of invention disclosures, patent applications and issued or granted patents, and the number of startup companies by department by year. These three variables represent publicly observable university tech transfer activities. While in some cases these may be counting the same underlying invention, each different observation represents an important progressive step toward commercialization, thereby giving more weight to those knowledge outputs that are presumably more significant.

3.2. Model Framework

The university knowledge production function developed here builds upon previous models (Griliches, 1979; Pakes and Griliches, 1980, 1984; Hausman et al, 1984; Hall et al, 1986; Jaffe, 1989; Pardey, 1989; Adams and Griliches, 1998) describing the technical relationship between

[15] Patent data was collected from the Thompson Innovation database by Thompson Reuters, searching for patents assigned to "Colorado State University".

[16] The data source is, again, the CSU Ventures office.

[17] The combined tech transfer metrics (TTM) index, $TTM_{i,t}=Invention_{i,t}+Patent_{i,t}+Startups_{i,t}$, consists of the sum of invention disclosures (*Invention*), patent apps or granted patents (*Patent*), and the number of CSU affiliated startup companies (*Startups*), for department *i* in time period *t*.

research inputs and outputs, structurally analogous to the neoclassical production function. Equation (1) represents the empirical functional form for panel data analysis of the university knowledge production relating research inputs to outputs,

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

for i departments or research units and t time periods. Y is the vector of different types of university knowledge outputs, which may be considered co-products of a common KPF. R represents research expenditures made by the i^{th} department in the current time period t and in each of k previous time periods. $\varepsilon_{i,t}$ is an independent and identically distributed panel disturbance term. The Y are discrete, taking on a finite number of non-negative, integer values. For such count data, the Poisson and negative binomial maximum likelihood estimation (MLE) models are well established, with the negative binomial better suited when the data is over-dispersed (Hausman et al, 1984; Hall et al, 1986).

3.2.1. Polynomial distributed lags (PDL)

Prior studies have established that research expenditures are the main input of knowledge production and have used a distributed-lag model to relate a finite number of k prior years' inputs of research expenditures to a given year's measured output of new knowledge. Some prior studies adopted an *ad hoc* distributed-lag model, which does not assume any *a priori* restrictions, such as systematic patterns of slope coefficients or a maximum length of the lag, but rather allows for a form-free lag structure. We observe in Fig. 2 that the estimated slope coefficients of the lagged input variables in Pakes and Griliches (1984) and Pardey (1989) appear to follow something more like a third or fourth degree polynomial. This suggests that the slope coefficients in both papers could be approximated by a suitable degree polynomial. In light of this observation, we instead follow Crespi and Geuna (2008) and adapt Almon's (1965) lag scheme with a polynomial of degree m and k periods of lagged inputs for our empirical specification of the knowledge production function, which enables us to find a best fit. Other alternatives—such as *ad hoc*, Koyck, and binomial lag schemes—are either non-restrictive or too restrictive. [18]

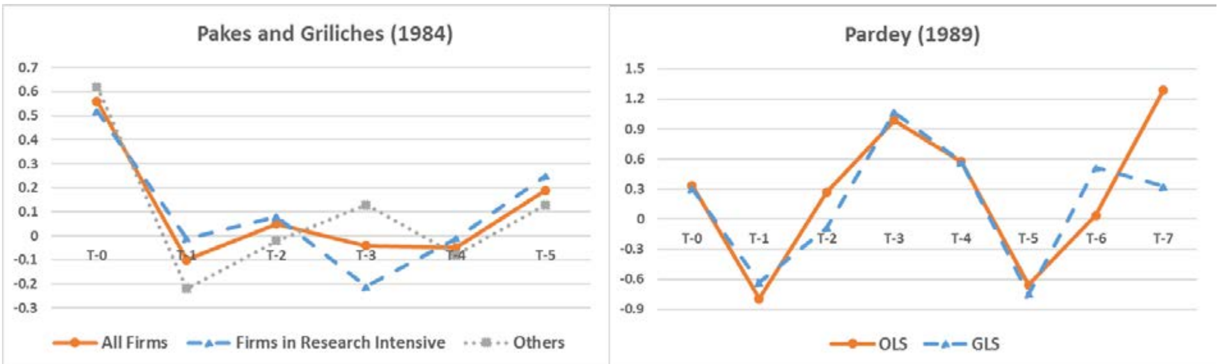

Fig. 2. Coefficient patterns of Pakes and Griliches (1984), and Pardey (1989)

A panel count polynomial distributed-lag (PDL) model is derived from equation (1) for negative binomial maximum likelihood estimation (MLE). Equation (2) is a PDL scheme in which the maximum degree, m, of the polynomial, p=0,1,2,...,m, must be smaller than the maximum lag, j=0,1,2,…,k, (m<k).

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

The corresponding unrestricted PDL equation of m-degree and k-lags is

$$\mathrm{Y}_{i,t} = \alpha + \sum_{p=0}^{m} \omega_p Z_{p,i,t} + \varepsilon_{i,t} \tag{3}$$

where $Z_{0,i,t} = \sum_{j=0}^{k} j^0 \cdot R_{i,t-j}$, $Z_{1,i,t} = \sum_{j=0}^{k} j \cdot R_{i,t-j}$, $\cdots$, $Z_{m,i,t} = \sum_{j=0}^{k} j^m \cdot R_{i,t-j}$

and the R are research expenditures indexed by academic department and year. The choice of degree of the polynomial, m, and the number of lagged years, k, to include, can be informed by two common measures for comparing maximum likelihood models, the Akaike information criterion (AIC) and the Schwarz-Bayesian information criterion (SBIC). The slope coefficients,

[18] While the *ad hoc* lag scheme follows no a priori restrictions, Koyck and binomial lag schemes are too restrictive since they assume, respectively, that all slope coefficients decline geometrically or follow quadratic patterns. See Ravenscraft and Scherer (1982) or Crespi and Geuna (2008).

ω_p, in equation (3) are not the true estimated slope coefficients of the unrestricted PDL model. Instead, the true slope coefficients need to be recovered from the PDL system (see Gujarati 2004, p. 688-690).

While the unrestricted PDL model has no *a priori* restrictions, a PDL model can have endpoint restrictions in which coefficients of the current and all beyond the k^{th} lagged input variable are held to be zero. When imposing this restriction on the coefficient of the current time period's input variable, it is called a left restriction or a near-end restriction. When imposing the restriction on the coefficient of the k^{th} and greater lagged input variables, it is called a right restriction or a far-end restriction. Following Gujarati (2004), such restrictions may be due to psychological, institutional, or technical reasons. In this analysis, we test a restricted PDL model in which inputs beyond the k^{th} lagged year no longer impact the current research outputs but research expenditures in the current year do have impact. The true slope coefficients of the restricted PDL model are recovered in much the same manner as in the unrestricted model. In knowledge production, there is no doubt that past research expenditures impact current research outputs, but how these may be limited depend on the type of research output, the inherent characteristics of the research environments, and the different purposes of R&D projects.

3.2.2. Effective labor in knowledge production

In the university context, research expenditures and full time equivalent (FTE) researchers might be considered the main inputs in the knowledge production function. However, since, most of the research expenditures go towards the salaries of the FTE researchers, there is reason to be concerned that these two input variables may interact with each other. Thus, we introduce an alternative for considering FTEs while avoiding such problems.

In Romer's (1986, 1990) specification of endogenous technological change, the stock of human or knowledge capital determines the rate of growth and is a non-rival and semi-excludable resource. These aggregate growth models, based on the notion of the production function, and therefore sometimes called "*the microfoundations of macroeconomics*", assume constant returns to scale instead of diminishing returns to scale, as in individual firm production functions. However, if we follow this line of reasoning and assume constant returns to scale with respect to labor (see Solow, 1956) in the university KPF, we can generate

$$\ln\left({Y_{i,t}}/{L_{i,t}}\right) = \alpha + \sum_{j=0}^{k} \beta_j \cdot ln\left({R_{i,t-j}}/{L_{i,t}}\right) + \varepsilon_{i,t} \tag{4}$$

where L is the count of full-time-equivalent (FTE) researchers, as a measure of human capital.

Assuming a Cobb-Douglas functional form, and taking the logarithm of both sides, we can denote research output per unit of effective labor (in our case, per FTE) as a function of research expenditures per unit of effective labor (per FTE). It should be noted that equation (4) is still a panel group fixed-effects model with polynomial distributed lags (PDL) of past research expenditures, but it is not a negative binomial MLE. Instead it is estimated as a log-linear model.

4. Results

We seek to test the effects of changes in research inputs on the various types of knowledge output as co-products of university research three sets of empirical relationships: (1) knowledge outputs disseminated via the public domain (published articles); (2) knowledge outputs disseminated via interpersonal contact that occurs in the context of university-industry collaboration; and (3) knowledge outputs disseminated via the more formal contractually based technology transfer mechanisms of patent licensing and venture creation.

We initially tested these relationships as a system of equations, using an effective labor log-linear seemingly unrelated regression (SUR) model[19], but preliminary results indicated that the error terms were uncorrelated among the equations for the three different types of research outputs. Thus, we do not adopt a system of equations approach, and instead we investigate independent regression models for each of the research outputs separately. However, as we will see in a later section, it may still be meaningful to describe the multiple outputs of university research as co-products.

Given the inherent characteristics of panel data analysis, in that it contains both cross-section and time-series, two significant issues that must be controlled for are heteroscedasticity and autocorrelation, respectively. Augmented Dickey-Fuller (ADF) results of unit root tests, by four different methodologies, indicate a stationary process for the input and output variables summarized in Table 1. And, the negative binomial maximum likelihood estimation has the advantage of controlling for heteroscedasticity.

4.1. Estimating the production of knowledge outputs disseminated via the public domain: published journal articles

Published journal articles are the primary output of knowledge production across the various departments and other research units of the university. Both Pardey (1989) and Adams and Griliches (1998) find journal articles to be increasing in research expenditures, with some lag. The total count of published journal articles by CSU authors from 1989 to 2012 was 37,029, compared to just 1,470 invention disclosures and 160 patent filings over the same time period. (See Table 1.) Moreover, the distribution of the publications across departments is skewed toward a relatively small number of departments.

[19] Four sets of independent regression models, the effective labor model with bootstrapped standard errors, one each for publications, collaboration index, and tech transfer metrics.

Table 2
Regression results for knowledge outputs measured by published journal articles, at the department and research unit level, 1989-2012

Dependent variable: Published Journal Articles				
	Ad-hoc[1] (k=6)[2]	Unrestricted PDL (k=6, m=2)[2]	Restricted PDL (k=6, m=2)[2]	Effective labor Unrestricted PDL (k=6, m=2)[2]
	[1]	[2]	[3]	[4]
Negative Binomial	YES	YES	YES	NO
Group Fixed Effects	YES	YES	YES	YES
Expenditure _t-0	0.0472***	0.0369***	0.0248***	0.0689
	(0.0129)	(0.0068)	(0.0064)	(0.0476)
_t-1	−0.0129	0.0091***	0.0172***	0.1054**
	(0.0166)	(0.0035)	(0.0027)	(0.0475)
_t-2	−0.0024	−0.0074	0.0109***	0.1270**
	(0.0168)	(0.0049)	(0.0008)	(0.0525)
_t-3	−0.0043	−0.0124**	0.0060***	0.1338***
	(0.0176)	(0.0053)	(0.0021)	(0.0463)
_t-4	−0.0037	−0.0059*	0.0025	0.1259***
	(0.0186)	(0.0036)	(0.0030)	(0.0326)
_t-5	−0.0213	0.0120***	0.0003	0.1031**
	(0.0189)	(0.0042)	(0.0029)	(0.0496)
_t-6	0.0758***	0.0413***	0.0338***	0.0656
	(0.0207)	(0.0113)	(0.0110)	(0.1074)
Sum of the lags	0.0786***	0.0736***	0.0956***	0.7297***
	(0.0060)	(0.0052)	(0.0129)	(0.1405)
Mean lag	3.6215	3.1399	2.8398	2.9786
Constant	2.2490***	2.2514***	2.2463***	2.0077***
	(0.0848)	(0.0845)	(0.0840)	(0.5708)
AIC[3]	5764.0	5760.9	5773.2	976.0
SBIC[4]	5802.8	5780.4	5787.8	990.2
Log-likelihood	−2873.9	−2876.5	−2883.6	−485.0
Observation	954	954	954	848
Group	53	53	53	52

1. Ad-hoc distributed lag scheme, which is not a PDL model, but follow previous studies; 2. *k* is the length of lags and *m* is the degree of polynomial; 3. Akaike Information Criterion; 4. Schwarz' Bayesian Information Criterion; Parentheses are standard errors; *** at 1%, ** at 5%, and * at 10% level of statistical significance.

Table 2 displays the results of the panel estimation of the KPF resulting in the output of published journal articles by the 54 departments and research units of the university from 1989 to 2012using four different models: model 1 can be denoted an *ad hoc* distributed lag scheme, comparable to those used in previous studies (Pakes and Griliches, 1980, 1984; Pardey, 1989); model 2 is an unrestricted polynomial distributed lag (PDL) scheme; model 3 is a restricted PDL with an end-point restriction; model 4 is a log-log model with PDL scheme and White's robust standard error, *a.k.a.* an effective labor model. Again, models 1 through 3 are negative binomial maximum likelihood estimations (MLE), but model 4 is log-linear.

In choosing the number of lagged years, *k*, and the degree of the polynomial, *m*, the preferred model is the one with minimum values of the AIC and SBIC. Further, we assume that the coefficient on the k^{th} lagged variable, at the end of the lag window, must be statistically significant at least at the 5% level and that *k* cannot be greater than 10 years, to prevent loss of degrees of freedom. As indicated in

Table 2, in the publications model the best fit is obtained when the maximum lag of research expenditures is 6 years (k=6) and with a second-degree polynomial (m=2).

Overall, models 2 through 4, using the PDL scheme of lagged research expenditures, have more statistically significant estimated slope coefficients and better model specification as indicated by the information criteria (AIC and SBIC), compared to the *ad hoc* model.[20] Interestingly, in the *ad hoc* model, coefficients on lagged research expenditures are not statistically significant in the middle time periods, from lagged years 1 to 5, similar to results in Pakes and Griliches (1980, 1984) and in Pardey (1989). These results generally conflict with intuition about the effects of changes in research funding. However, in the other three models we find lagged research expenditures during the crucial time period of 1 to 5 years are statistically significant, particularly in the effective labor PDL, model 4.

In model 3, the restricted PDL model, estimation results indicate that only a few years' expenditures—those made in the current through the third lagged years—strongly and positively affect the current year's publication counts. In model 4, the effective-labor PDL model, estimation

[20] Model 4, the effective labor model, cannot be directly compared with the other models using the information criteria, because it is a log-log model whereas the others are negative binomial MLE.

results indicate that the most recent six years' research expenditures (per FTE) have a positive and significant effect on current publication counts (per FTE).

The sum of the estimated coefficients represents the long-run or total impact of past and current research expenditures on a current year's publications. It indicates how publications by department change in response to prior years' changes in research expenditures. The sum of the coefficients in all four models are statistically significant: research expenditures have a positive and significant long-run impact on publication counts, at the departmental level, according to all four models.

These results also shed light on the nature of the time lags between research expenditures and resulting publications. The mean lag[21] is a weighted average and this corresponds, for example, to the average duration between a research project's inception and completion.[22] The unrestricted PDL model [2] indicates that, on average, a university research team spends 3.14 years in generating a publication from a given round of research expenditures: similarly, the restricted PDL model [3] finds a mean lag of 2.84 years; the *ad hoc* model [1], 3.62 years; and the effective labor PDL model [4], 2.98 years.

However, there are reasons to focus on the restricted PDL model in evaluating the mean lag. Given its end point restriction, the restricted PDL model is not affected by spurious lag effects from more distant prior years' expenditures. Thus, the estimate of 2.84 years in model 3 is likely a more reliable mean lag than those estimated by the other models. By comparison, in previous studies, Pardey (1998) finds a mean lag of citation-adjusted publications is 3.87 years in his OLS model, 3.30 years in his "within" model, 4.64 years in his "between" model, and 3.62 years in his

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[21] It can be calculated as $Mean\ lag = \frac{\sum_0^k k \cdot |\beta_k|}{\sum_0^k |\beta_k|}$

[22] In practice, actual expenditures typically begin some time after project inception, due to the time involved in applying for and receiving funding. While similarly, publications occur some time after project completion, due to time involved in submission, review, revision, and publication of academic journal articles.

EGLS model. In Crespi and Geuna (2008), their unrestricted PDL model shows a mean lag of 3.48 years and their restricted PDL model, 4.16 years. Thus, this analysis finds a somewhat smaller mean lag than previous studies. The differences in lag may be related to differences in level of analysis: this study uses data at the departmental level, while Pardey analyzes data at an institutional level, and Crespi and Geuna use data aggregated at a national level.

Since models 1, 2, and 3 are negative binomial MLEs, their slope coefficients do not directly reveal marginal effects. Rather, marginal effects need to be calculated by an incident rate ratio (IRR). However, in model 4, the log-linear effective labor PDL model, each coefficient directly indicates the marginal effect. We find that elasticity of publication output relative to research expenditures made in each lagged year increases from the current year until the third lagged year, which implies that research expenditures in the third lagged year have maximum impact on the current year's journal publications.

4.2. Estimating the production of knowledge outputs disseminated via university-industry collaboration, as measured by the combined collaboration metric

Table 3 presents regression results for the relationship between the common input variable of research expenditures and, in this section, those knowledge outputs measured by the combined collaboration metrics, at the department level, from 1989 to 2012. The set of models estimated is the same as in the previous section: [1] *ad hoc*, [2] unrestricted PDL, [3] restricted PDL, and [4] effective labor. However, the best fit is found when considering several more lagged years, when k=9, and when fitting a second degree polynomial, m=2. Similar to the estimation results in the previous section, all of the PDL models (models 2, 3, and 4) have better fit than the *ad hoc* model [1]. The unrestricted PDL, model 2, indicates that the current and the previous years' level of research expenditures positively affects the current year's collaboration-mediated outputs. The restricted PDL model [3] and the effective labor PDL model [4] are largely in agreement indicating positive effects from the most recent five years' research expenditures.

Table 3
Regression results for knowledge outputs measured by the combined collaboration metric, at the department and research unit level, 1989-2012

Dependent variable: Collaboration Index	Ad-hoc[1] (k=9)[2]	Unrestricted PDL (k=9, m=2)[2]	Restricted PDL (k=9, m=2)[2]	Effective labor Unrestricted PDL (k=9, m=2)[2]
	[1]	[2]	[3]	[4]
Negative Binomial	YES	YES	YES	NO
Group Fixed Effect	YES	YES	YES	YES
Expenditure_t-0	0.0587**	0.0372***	0.0270***	0.1317
	(0.0277)	(0.0112)	(0.0112)	(0.0922)
_t-1	−0.0035	0.0158**	0.0218***	0.1697***
	(0.0391)	(0.0067)	(0.0065)	(0.0547)
_t-2	0.0124	0.0006	0.0171***	0.1871***
	(0.0460)	(0.0066)	(0.0028)	(0.0543)
_t-3	−0.0066	−0.0085	0.0130***	0.1837***
	(0.0402)	(0.0078)	(0.0016)	(0.0677)
_t-4	0.0187	−0.0114	0.0095***	0.1598**
	(0.0358)	(0.0080)	(0.0033)	(0.0746)
_t-5	−0.0348	−0.0082	0.0065	0.1152
	(0.0380)	(0.0068)	(0.0047)	(0.0708)
_t-6	0.0263	0.0012	0.0041	0.0499
	(0.0647)	(0.0053)	(0.0054)	(0.0596)
_t-7	−0.0788	0.0167**	0.0022	−0.0360
	(0.0610)	(0.0075)	(0.0052)	(0.0571)
_t-8	0.0098	0.0384***	0.0009	−0.1425
	(0.0622)	(0.0143)	(0.0043)	(0.0878)
_t-9	0.1311***	0.0662***	0.0327	−0.2697*
	(0.0565)	(0.0239)	(0.0167)	(0.1479)
Sum of the lags	0.1332***	0.1479***	0.1349**	0.5490*
	(0.0211)	(0.0211)	(0.0180)	(0.2945)
Mean lag	5.9491	5.6615	3.7660	4.4481
Constant	0.7913***	0.7558***	0.8366***	−0.6184
	(0.1245)	(0.1225)	(0.1185)	(0.9869)
AIC[3]	2775.2	2767.5	2773.8	821.6
SBIC[4]	2824.9	2785.6	2787.3	834.1
Log-likelihood	−1376.6	−1379.8	−1383.9	−407.8
Observation	675	720	720	487
Group	45	45	45	43

1. Ad-hoc distributed lag scheme, which is not a PDL model, but follow previous studies; 2. *k* is the length of lags and *m* is the degree of polynomial; 3. Akaike Information Criterion; 4. Schwarz' Bayesian Information Criterion; Parentheses are standard errors; *** at 1%, ** at 5%, and * at 10% level of statistical significance.

The sum of the estimated coefficients, reflecting the total or long-run effect indicate that, overall, research expenditures have a net positive impact on the university knowledge outputs disseminated via the collaboration mechanism, with at least a 1 percent level of statistical significance across all four models. Mean lags, interpreted to represent the average duration between research expenditure and the outputs measured (or at least proxied) by the combined collaboration metrics, are 5.95 years in the *ad hoc* model [1]; 5.66 years later in the unrestricted PDL [2]; 3.77 years in the restricted PDL [3]; and 4.45 years later in the effective labor model [4].

4.3. Estimating the production of knowledge outputs disseminated via patent licensing and venture startups, as measured by the combined technology transfer metric

Third, we estimate the production of knowledge outputs that are disseminated via technology transfer activities using, again, the same empirical regression models and independent variables employed in the previous two sections, even though the overall magnitude of tech transfer activities is considerably smaller. The total number of invention disclosures from 1989 to 2012 was 1,470. Following the disclosure of an invention comes the decisions of whether to file a patent application, to start up a company, or both. The university's total count of patent applications filed from 1989 to 2012 was 160, and the university's total count of startups from 1989 to 2012 was 40. The distributions of patent filing and of the creation of startup companies are skewed toward a few colleges and departments, with departments in the three leading colleges accounting for over 80 percent of both measures.

Conversely, the number of invention disclosures, patent filings, and startups by the remainder of academic departments is usually zero in a given year, and thus these individual variables cannot be estimated without a zero-inflated count model regression procedure. Instead, we create a linear combination of these three metrics into a single variable, which exhibits relatively fewer zero values. This linear combination of the tech transfer metrics introduces a degree of multi-counting of single inventions (as the technology transfer process may, in some cases, consist of invention disclosures, patenting procedures, and a startup company, all around a single invention.) However, we can interpret this combination of metrics to simply give more weight to those inventions that proceed further through the typical technology transfer process.

As displayed in Table 4, the three PDL models ([2], [3], and [4]) exhibit better goodness of fit than the *ad hoc* model ([1]). In model 2, the unrestricted PDL, estimated coefficients from the current year's to the 3rd lagged year's research expenditures are positive and significant. Similarly, in model 3, the restricted PDL, research expenditures from the current year through the 3rd lagged year also have positive and significant impacts on the current year's tech transfer activities, but research expenditures from years prior appear to have insignificant or negative influence. The negative relationship indicated in all four models over longer time periods could be an artifact of a major restructuring of the university's tech transfer office undertaken in 2007, prior to which levels of invention disclosures, patent filings, and startups were relatively low, even though research expenditures were already growing rapidly, but after which the expected positive relationship was restored and continued until the end of the study's time period in 2012.

Overall, the total or long-run impact of research expenditure inputs on the combined tech transfer metrics output is not significant in models 1 and 2, but it is positive and significant in models 3 and 4. Mean lags indicate that the average duration between making research expenditures and the observation of an invention disclosure, patent filing, or startup is 4.98 years in the *ad hoc* model, 4.56 years in the unrestricted PDL model, 4.48 years in the restricted PDL model, and 4.81 years in the effective labor PDL model. According to tech transfer survey data analyzed by Heher (2007), the average time between invention disclosure and a final patent granted is about five years.

Table 4

Regression results for knowledge outputs measured by the combined tech transfer metrics, at the department and research unit level, 1989-2012

Dependent variable: Combined Tech Transfer Metrics	Ad-hoc[1] (k=9)[2]	Unrestricted PDL (k=9, m=2)[2]	Restricted PDL (k=9, m=2)[2]	Effective labor Unrestricted PDL (k=9, m=2)[2]
	[1]	[2]	[3]	[4]
Negative Binomial	YES	YES	YES	NO
Group Fixed Effect	YES	YES	YES	YES
Expenditure_t-0	0.0969**	0.0487***	0.0555***	0.0432
	(0.0396)	(0.0167)	(0.0156)	(0.1331)
_t-1	−0.0153	0.0440***	0.0371***	0.2031**
	(0.0590)	(0.0100)	(0.0090)	(0.0932)
_t-2	0.0837	0.0372***	0.0216***	0.3095***
	(0.0630)	(0.0099)	(0.0037)	(0.0839)
_t-3	−0.0857	0.0285**	0.0089***	0.3622***
	(0.0623)	(0.0118)	(0.0022)	(0.0891)
_t-4	0.1102	0.0178	−0.0009	0.3613***
	(0.0550)	(0.0121)	(0.0049)	(0.0915)
_t-5	−0.0164	0.0050	−0.0079	0.3069***
	(0.0543)	(0.0104)	(0.0069)	(0.0847)
_t-6	0.0741	−0.0097	−0.0120	0.1988***
	(0.0903)	(0.0081)	(0.0078)	(0.0709)
_t-7	−0.0336	−0.0264**	−0.0133*	0.0372
	(0.0911)	(0.0109)	(0.0076)	(0.0665)
_t-8	0.0308	−0.0452**	−0.0117*	−0.1780*
	(0.0939)	(0.0207)	(0.0062)	(0.0985)
_t-9	−0.2066**	−0.0659*	0.0767***	−0.4469***
	(0.0847)	(0.0348)	(0.0235)	(0.1645)
Sum of the lags	0.0382	0.0341	0.1540***	1.1973***
	(0.0291)	(0.0270)	(0.0229)	(0.3600)
Mean lag	4.9756	4.5598	4.4754	4.8171
Constant	0.5143**	0.5586***	0.4422**	0.2890
	(0.2091)	(0.2029)	(0.1879)	(1.1219)
AIC[3]	1364.2	1356.6	1357.5	500.8
SBIC[4]	1412.3	1374.1	1370.6	511.6
Log-likelihood	−671.1	−674.3	−675.8	−247.4
Observation	585	585	585	274
Group	39	39	39	39

1. Ad-hoc distributed lag scheme, which is not a PDL model, but follow previous studies; 2. *k* is the length of lags and *m* is the degree of polynomial; 3. Akaike Information Criterion; 4. Schwarz' Bayesian Information Criterion; Parentheses are standard errors; *** at 1%, ** at 5%, and * at 10% level of statistical significance.

However, according to Graff, Heiman, and Zilberman (2023) licensing or startup negotiations are typically conducted in parallel with patent prosecution and are often completed before a final patent issues. Thus, mean lags computed from the estimates here are certainly reasonable.

5. Discussion

5.1. Returns to Scale in Knowledge Production

The knowledge production function is based on neoclassical production theory, wherein it is assumed the main objective of a producer is to maximize the difference between revenues and costs involved in turning inputs into outputs. The production function, as such, necessarily exhibits certain characteristics, such as non-negativity, weak essentiality, and concavity. However, because knowledge is an intangible asset and because a research university does not necessarily pursue a profit maximization objective, not all of the typical characteristics and assumptions of neoclassical production theory necessarily hold when describing the relationships between university research inputs and outputs.

Since publications represent the most common knowledge output of the university, it is more likely that the production of publications has been optimized and, therefore, may exhibit neoclassical production theory's law of diminishing marginal returns. Adams and Griliches (1998) find output of journal publications to exhibit constant returns to scale at the aggregate level but decreasing returns to scale at the individual university level. Decreasing returns to scale (DRTS) is indicated when the sum of all slope coefficients is significantly less than one: $\sum_{j=0}^{k} \beta_j < 1$. In our analysis, in the effective labor model[23] of published journal articles, the sum of all lagged year coefficient estimates is 0.7297 and the sum of just those coefficient estimates that are significantly greater than zero is 0.5952 (from model 4 in Table 2) indicating DRTS. Similarly, the sum of estimated slope coefficients in the effective labor PDL model of the collaboration metrics output (model 4 in Table 3) is 0.5490 for all estimated coefficients and 0.7003 for just those coefficients that are significantly greater than zero, indicating the output of knowledge disseminated via collaborative mechanisms also exhibits DRTS. In contrast, the sum of coefficients in the effective labor PDL model of the tech transfer metrics output (model 4 in Table 4) is 1.1973 for all estimated coefficients and 1.7419 for just those coefficient estimates that are significantly greater than zero, indicates increasing returns to scale (IRTS). Generally interpreted, a doubling in research inputs would lead to less than a doubling of the outputs disseminated via the public domain or via industry collaboration but would lead to more than a doubling of the tech-transfer-mediated knowledge outputs in the long run.

We must caution that, in terms of creating new knowledge associated with each of these alternative mechanisms of dissemination, the assessment of productivity is complicated, especially in an empirical study, by variations in institutional conditions as well as intrinsic propensities of researchers to engage in what might be perceived as more commercially-oriented research activities across different disciplines, fields, technologies, and industries. In addition, biases may be introduced from the different proxy variables, due to the skewed distribution of observations across departments, or the linear combinations of these proxy variables. Nevertheless, these results

[23] In order to compare research productivity across the three different types of research outputs, the effective labor log-linear model [4] is more appropriate, because estimated slope coefficients interpreted as marginal effects directly, representing output elasticities with respect to each of the lagged values of research expenditure.

provide some indication that productivity of university research, at the scale observed here, may vary across the different types of knowledge outputs as disseminated via these different channels.

5.2. Interrelationships among the Different Types of University Research Outputs

While productivity and returns to scale is informed by the sum of estimated coefficients, more nuanced insights can be gleaned by comparing the patterns of the estimated coefficients across the three systems. Fig. 3 plots the coefficient point estimates on lagged research expenditures from the effective labor model for each of the knowledge output measures (model 4 in Table 2, Table 3, and Table 4) which, again, directly indicate marginal effects. The slope coefficients in all three models follow broadly similar inverted-U-shape or concave patterns over time.

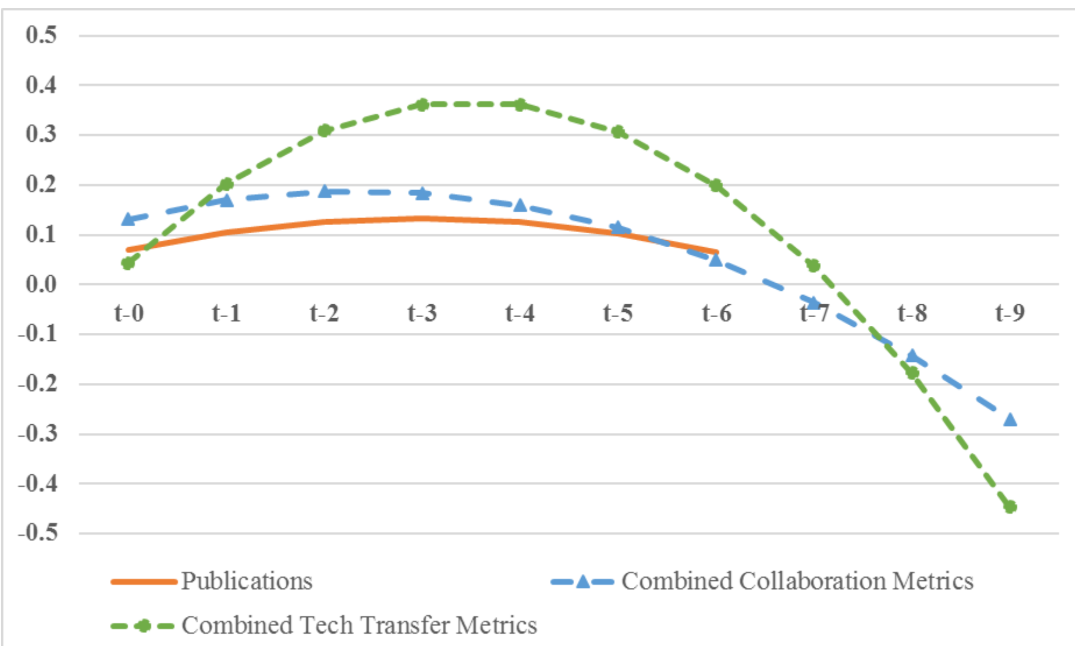

Fig. 3. Comparison of estimated slope coefficients of three research outputs in each effective labor PDL log-linear model (degree of polynomial m=2 in all three models)

Given this concave pattern, we can observe not just the sums of the coefficients (essentially, the area under each curve in Fig. 3) indicating the returns to scale (as in the previous section), but we also can observe their average values over time, their maximum value and when it occurs, as well as their weighted average over time, i.e. the mean lag, as was calculated for each type of output in Section IV above.

Based on these patterns, we see that publications reach maximum output around the third year after research expenditures. This corresponds with the mean lag for publications which was calculated as 2.98 in the effective labor PDL model. The maximum coefficient value, at 0.1338 (in the 3rd lagged year) is not much greater than the average coefficient value of 0.1042 over all lagged years.

Collaboration outputs reach a maximum somewhat earlier than publication outputs, peaking sometime in the second to third years after research expenditures are made. This is much shorter timeframe than the mean lag computed for the combined collaboration metrics in Section IV above of 4.45 years. Moreover, the maximum coefficient value of 0.1871 (in the second lagged year) is considerably higher than the average coefficient value of 0.0549.

The combined tech transfer metric is most responsive to changes in research expenditures, with a much greater maximum value, at 0.3622, and a higher average coefficient value, at 0.1197, than the other two types of knowledge output. These observations correspond to the higher sum of estimated coefficients and the conclusion that technology transfer outputs appear to exhibit IRTS in the long run. Also, the maximum coefficient value occurs somewhat later, in the third to fourth years after research expenditures are incurred, closer to the calculated mean lag of 4.81 years.

The timings of these coefficient maxima are intuitive. Knowledge disseminated through collaboration tends to arise earliest, during the actual process of conducting R&D. Output of knowledge via publications takes more time, due to the editorial review process. Knowledge output via technology transfer can take longer still, due to the inherent lags involved in patent prosecution as well as in both license negotiation and firm startup processes.

Unfortunately, it is not possible to directly evaluate the co-product relationship among the three knowledge outputs using the pattern of lagged slope coefficients in Fig. 3, due to the departure of knowledge production from some of the assumptions characteristic of physical production. If the three independent effective-labor PDF models were for three physical co-products from a set of factories or farms, the production possibility frontier (PPF) for the physical co-products would be defined, each slope coefficient would indicate a *marginal physical product* (MPP) for that co-product, and the *rate of product transformation* (RPT) or *opportunity cost* of production of one output relative to another, given the level of inputs, could be written as $dy_2/dy_1 = -(MPP_2/MPP_1)$. If the RPT is positive (negative) the outputs would be said to be *complements* (*substitutes*) in production. In our results, since all slope coefficient in the three systems have the same sign up through the 6th lagged year, this means that all RPTs are negative and all possible pairwise relationships among the three outputs would be said to be substitutionary.

However, unlike physical production where mapping of inputs to outputs is largely deterministic (planting more corn than soybeans tends to produce more corn than soybeans), the output of a given type of knowledge from a knowledge production process is, to a certain degree, stochastic. Researchers may declare their intentions at the outset of a research project, but they cannot control, with certainty, the quantities or proportions of publishable findings versus tacit results versus patentable inventions that will result. Moreover, intuitively, production of more of one type of output does not necessarily result in fewer of another; indeed, the opposite can be imagined just as easily: with success in producing one type of knowledge output actually increasing the probability of producing more of the others. Considering knowledge production in these terms, the patterns in Fig. 3 can be consistent with a story of complementarity among all three types of knowledge output as co-products of a common set of research activities. This concurs with prior results in the literature that indicate pairwise complementarity or economies of scope between publications and patents (Agrawal and Henderson, 2002; Payne and Siow, 2003; Thursby and Thursby, 2011; Folz et al 2012), between publications and industry collaboration (Bonaccorsi, Daraio, and Simar, 2006), and between patent licensing and industry collaboration (Jensen and Thursby, 2001). Under these conditions, an increase in research expenditures results in increases in each of the three outputs, albeit in different magnitudes and over different timeframes.

6. Conclusion and Further Study

This study explores the research production and knowledge dissemination activities of the academic departments of a large public research university, developing a uniquely comprehensive institutional data set and new empirical techniques for estimating the knowledge production function. The dataset represents all of the departments or research units of the university, across all fields of study, over a fairly long time frame, and seeks to include all relevant research inputs and outputs. As such, it constitutes more than just a random sample or just a subset of disciplines.

We have utilized four different specifications of the knowledge production function (KPF) to estimate a group fixed-effects panel, using negative binomial maximum likelihood estimation (MLE) and log-linear effective labor models, with both *ad hoc* and with polynomial distributed lag (PDL) schemes relating past research expenditures to subsequent research outputs. We estimate these same four KPF models for each of three types of knowledge outputs independently. The estimates of the slope coefficients in the PDL models are statistically more significant (according to p values) and the model specification appears to be generally better (as indicated by smaller

AIC and SBIC values) than the *ad hoc* model, which is comparable to those used in the prior literature. After considering various input variables, we find research expenditures as a financial input and full-time equivalent (FTE) researchers as a labor input to be empirically significant explanatory variables, aligning our knowledge production function with neo-classical production theory. The effective labor PDL model gives what are perhaps the most intuitive results in this analysis of knowledge production, whether for investigating returns to scale, output elasticity, or the notion of knowledge co-products. The greatest advantage of the effective labor model is to control for lag effects of the FTE variable, following the labor-augmenting or Harrod-neutral approach, with knowledge and labor entering multiplicatively. Quality of human capital is generally unmeasurable in production function systems.

We see, even just from the summary statistics, that publications—or, more generally, increments of new knowledge disseminated via the public domain—are the most common output across all of the departments and research units of the university: The average number of publication by department in a year was 28, while the average collaboration metric value was about 6 (publication equivalents) and the tech transfer metric value was about 1 (invention disclosure, patent filing, or startup founding). And these measures are skewed: for most departments in most years published journal articles were the only research output observed. Also, in the estimated models, publications have the shortest mean lag length: the time between research project inception and the output of publications is one or two years shorter than the output of the other two knowledge types.

Production of knowledge disseminated via publications and the more traditional industry collaboration and extension activities appear to fit more closely the assumptions of classical production theory, including the law of diminishing marginal productivity or decreasing returns to scale with respect to the input of research expenditures. The other type of research output, knowledge disseminated via the newer, more formal technology transfer activities between university and industry, appear to exhibit increasing returns to scale. This result opens up questions about whether and how the creation of the kinds of knowledge that can be disseminated via formal IP-mediated tech transfer or entrepreneurial activities may enjoy cost advantages in the long run, and whether currently they may not be operating at efficient scale.

As for policy implications, several things stand out. First, those outputs of university knowledge production that are more commercially oriented (exhibit less public goods characteristics) are also found to be systematically related to the knowledge production inputs, much as are the university's public goods outputs. In other words, they do not appear as merely spurious, occasional byproducts. Their production can and should therefore be accounted for by the university and understood to be systematically related to university research activities. Second, tech transfer outputs are found to exhibit increasing returns to scale while the public-domain outputs exhibit decreasing returns to scale. This may imply a growth opportunity for university knowledge production activities increasing industry collaboration and tech transfer. Third, as implied by the fact that these different knowledge outputs can be characterized by their different dissemination or spillover mechanisms, there may be tradeoffs involved in the distribution of economic impacts as these different types of knowledge output grow at different rates from an increase in research inputs. Those outputs with less public-goods characteristics are more "sticky" and therefore deferentially result in regional economic impacts.

Despite interesting preliminary findings, one major issue for this study is its reliance upon a single institution's context and data. There are both advantages and disadvantages of focusing on just one or a handful of institutions, which others have confronted as well (see Agrawal and

Henderson, 2002, or Mowery et al, 2004, chapter 6). It may compromise generality; however, it does control for other institutional and regional characteristics, including overall levels of infrastructure, management skills, administrative policies, and so on. In future research, it will be valuable to collect more institutions' data at a similarly disaggregated level. Nevertheless, results of this analysis to be of value in future economic studies of university knowledge production, as well as of practical value to university administrators as well as policymakers.

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