Federal and Industrial Funded Research Expenditures and University Technology Transfer Licensing

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Abstract

I relate the numbers of university licenses and options to both university research characteristics and research expenditures from federal government or the industry. I use the polynomial distributed lag model for unbalanced panel data to estimate the effects of research expenditures from different sources on licensing activity. I find evidences suggesting both federal and industrial funded research expenditures take 2-3 years from lab to licenses while federal expenditures have higher long-term dynamic effect on number of licenses. Breaking down licenses by different types of partners, I find that federal expenditures have highest effect with small companies while industrial-funded expenditures have higher effect in licenses with large companies and licenses yielding large income. Further research is necessary to analyze the reason for such differences between the effects of research expenditures on licensing activity.

Keywords Science Policy; Technology Transfer; innovation; research expenditures; Universities

JEL Classification O31; O32; O38; I23; L31

I. Introduction

To justify the public funding for research, the knowledge generated from these scientific studies plays an important role. Since most of the results university research produced are published in academic journals without specific monetary or economic value attached to it, the output of academic research must use other measurable quantities. The intellectual properties produced by these research, while by no means represent the majority of the impact of university in the economy, have become an important marker for both measuring academic research output and understand the societal benefit generated by especially when university research often provides the basic scientific knowledge that drives other applications (Muscio, 2012).

There has been a substantial change in the management of intellectual property originates from research in the past three decades in the United States. Following the enactment of Bayh-Dole Act of 1980, the inventors of the inventions arise from federally-funded research were permitted to retain the patent rights provided that they are affiliated with universities, non-profit research institutions or small businesses. The Bayh-Dole act allowed the money from patents of university innovations to academic inventors and the institutions and academic partnerships with industry became commonplace. The Bayh-Dole act also facilitated the creation of Technology Transfer Offices (TTOs) in the research universities. TTOs specialize in representing the institution and academic inventors to negotiate the transfer of technology between academic institutions and the industry. The performance of TTOs has been hypothesized to directly correlate with its ability to successfully license the technology.

Two economic theories predict different societal welfare for the increased intellectual property application within academia. The of Bayh-Dole Act and intellectual property hypothesizes that in the absence of property rights (patents), both the private industry and academic inventors would be disincentivized to invest in innovation. Therefore the increase of licensing and patents would lead to a net welfare increase as the society benefits from the domestic commercialization of these inventions (Heisey, 2011). However, past studies have found it empirically difficult to find evidences to support this theory positively associating the licensing activity and social welfare.

On the other hand, other studies had suggested that the increase in transaction cost and access costs as a result of intellectual property may results in a welfare loss for the public. In addition, assuming universities administrators have the utility function to maximize the revenue of the institution, the licensing income may introduce bias in the decision making and direct administrators to encourage more research subjects in more patentable areas and to put less attention in areas less patentable and instruction (Just, 2006). In the long run, therefore, an increase in licensing activity reduces the societal welfare and the production of public good research.

To evaluate the theory relating to the university technology transfer and commercialization, I test various hypotheses about the university research expenditure, number of licenses and TTO characteristics. Firstly, the source of research expenditure may have different effect on the number of licenses executed by TTOs. Governmental funding agencies, such as the National Institute of Health (NIH) and National Science Foundation (NSF) of the United States, employ a two-stage peer-reviewing processes where the experts in both stages considers the scientific merits of the project and authors' qualification without explicitly considering the commercialization potential of research projects. Industrial funded research, on the other hand, will have a stronger emphasize on commercialization and patentability of the research subjects and leads to a larger number of licenses been executed. I then estimate the direct effect of research expenditure on licenses executed. In addition, I also investigated the lag between the research expenditures from various sources to the licenses been executed.

Secondly, we consider the effects of different university types and their influences on the total licenses executed. For example, an institute with a school of medicine may have more medical-related research projects and licenses whereas the land grant designation was given with an emphasis on public service (Heisey, 2011). I also examine the direct effect of the experiences and the size of TTOs and its effect on licenses as the ability of TTOs can directly affect the number of licenses executed.

Lastly, I examine the above relationship with licenses executed to different types of companies. A significant amount of technology transfers are licensed to "research-based academic spin-off companies" (RASOCs) which were startups established by faculty members. Past studies have found that these companies tend to focus on single project and facilitate the commercialization of the license faster than large companies (Vincett, 2010).

The rest of the paper is organized as follows. I first review the empirical literature on the university technology transfer, performance of TTOs and the academic research expenditure in the United States. Following that I will briefly describe our data source and different variables in Part III along with the empirical specification for the econometrics model I used in Part IV. The results are presented with several alternative estimation techniques in Part V. Lastly, the final section VI discusses the potential implications of our findings and concludes the paper.

II. Literature Review

A. Academic research expenditures and funding

The majority of the research funding in the United States for higher education institution research and development (R&D) comes from the federal government with its various agencies as shown in Figure 1. Industrial funded research expenditures have been consistently between 7-12% of that from the federal government. Federal government generally supports research through awards, contracts or grants to researchers while industry support research through sponsored research projects or corporate-sponsored research centers (CRS, 2012). Industry funding for research have been found to have mixed effects the output of publications by researchers in different studies but positive association with patent application (Hottenrott, 2011).

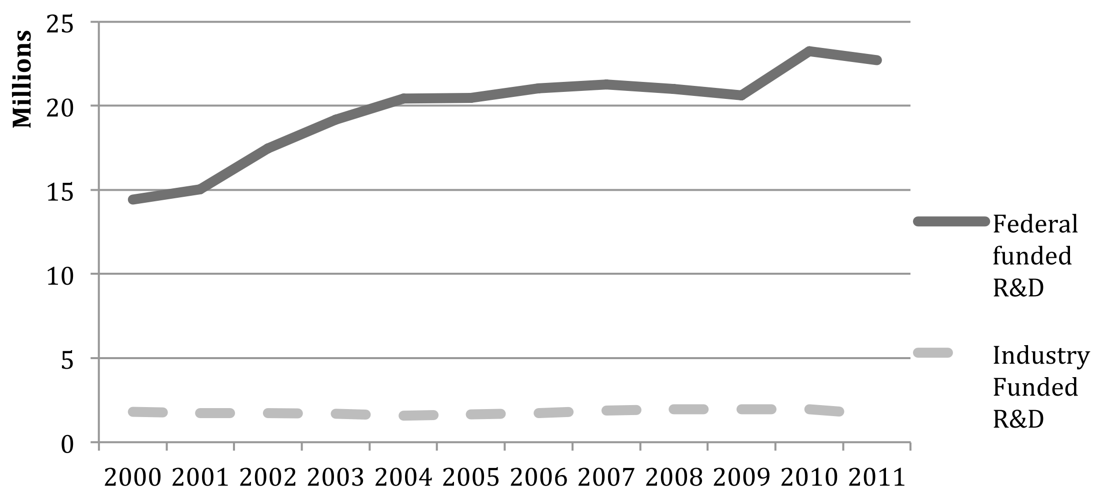

Figure 1 Trend of research expenditures (in 2000 dollars) in United States Higher Education Institutuions, by funding sources., 2000-2011
Source: NSF academic R&D expenditures survey

Industry and federal government also select projects to fund through different processes. While the industry identify the commercialization potential and application values of research projects or the value federal government utilizes a dual peer review process to evaluate research proposals. For example, the grant applications are first evaluated by a panel of non-government scientists in relevant areas, who gave a priority score for each new grants applications in the National Institute of Health. The applications with priority scores above certain pre-determined threshold are then forwarded to the one of the twenty-seven NIH institutes where a national advisory committee in that institute makes recommendations to the director of the institute to make final funding decisions. In both stages, the committees consider an application's significance, technical merit, innovativeness and investigators' qualifications. Although NIH implemented the science-driven funding mechanisms, past studies have found that the funding from NIH are influenced by other factors such as the state's congreemen membership of the Subcommittee of Labor, Health, and Human Services (LHHS) of the Committee on Appropriations in the House of Representatives (Hegde, 2009). In addition, the institutional characteristics of the grant applicant have been found to associate with funding decision. The sizes of the institution, which indicate the size of the peer groups for the scientists, have been found to positive associated with the funding outcomes within Germany (Grimpe, 2012). In the study, I first examined the funding from both federal and industrial sources relative to various institutional characteristics to identify the funding.

B. Complementarity Public Research Funding

In the classical economic theory, public research funding for biomedical R&D can be complement or substitute to the private R&D funding. Public research often serve as the financial support for the initial phase of research in basic biomedical or pharmaceutical sciences before the technologies that have commercialization potential attract private investments. The empirical model of pharmaceutical R&D postulated that the level of private investment are affected by the interaction between marginal cost of capital (MCC) and marginal rate of return (MRR). Factors changing the MCC include the availability of funds, interest rates. Demand determined the MRR, including factors such as health status, FDA regulatory standards and public scientific knowledge (Toole, 2007). The basic assumption of this model is the interaction between public research funding for basic research and the private investment in clinical or later-stage developments. The lag between the two can be measured by OLS, although the multicollinearity between different time lag dependent variables may produce imprecise results and require correction. Therefore, a finite-distributed lags model for two stages may be required to reduce the multicollinearity, which is called Almon lags (Toole 2007). The lags coefficient can be positive (investment stimulating) or negative (investment saving), which can also be viewed as an indicator for the complementarity or substitutability between public and private R&D spending. In multiple previous studies, studies have found that there exist a strong complementary relationship between private and public R&D funding in difference science disciplines, including pharmaceutical research, in both US and other European countries (Muscio 2013; Toole 2007; Blume-Kohout 2012). Some studies have used the lags between the basic research funding and late-stage developments as the end points for the lag model, such as clinical trials or new molecule entity approval dates. The complementarity of public research funding and private investments may indicates that public research funding have a larger effects in the initial commercialization of technology from university whereas private industrial funding are more critical in later-stage.

In some cases, the complementarity is even more critical. For example, to develop new technology or novel pharmaceuticals for Neglected diseases (NDs) requires the public research funding to seed most of the initial researches. NDs are typically defined as the diseases that create disproportional impact, in the form of mortality and morbidity, on low- and middle-income countries relative to high-income countries. While there is little consensus on the exact list of NDs, the majority of NDs is unable to attract private investments due to the affected population's low ability to pay (Moran, 2009). The World Health Organization describes NDs as being strongly associated with poverty, and flourish in impoverished and tropical environments (Cloyd, 2012). Thus, if we imagine the pharmaceutical development process as solving jigsaw puzzles for different diseases, private investment would provide to resources to solve existing puzzles while public research funding are required for the genesis of new puzzles to solve (Toole 2007). NDs need the public research funding to first present it as a puzzle to attract more private and public research spending to solve the puzzle. Therefore, NDs are a class of diseases, which its treatments, in lieu of any other secondary uses in other indications, are, by definition, strong complements to private investments. In addition, the scarcity of ND research funding may influence the NIH funding decisions, as more application-based proposals may be more effective than basic science based applications. The focus on application-based research can introduce a shorter time lag for NDs relative to other disease funding.

C. University Technology Transfer

As the US economy become increasingly dependent on the knowledge production as the primary driver for growth, universities played an important role in the genesis of new technical knowledge in the economy and can be viewed as a university technology commercialization (UTC) industry (Cardoza, 2010). The outputs of the industry are primarily intellectual properties, especially patents, to firms in other industry. Bayh-Dole act was specifically designed encourage the commercialization of university developed technology, and to facilitate the market entry of the product. The act allows the inventors with federal grants to assert patent rights in their inventions without giving up the patents to the government, more institutions started to actively manage their intellectual property by establishing TTOs. The typical value chain in technology transfer is the transformation of research into invention disclosures, invention disclosures into patents, patents into licenses and finally licenses into income. It typically takes between \$1.5 million dollars to \$3 million dollars in basic research expenditure to generate one invention disclosure (Thomas, 2007). There exist large fallout along the value chain. Only 15% of the invention disclosures (with patents) will be licensed for further development and commercialization. Only a small fraction (2% of licenses; 0.1-0.2 % of invention disclosures) of research projects eventually achieves commercial success and generates >\$100,000 dollars royalties to the university and the inventor. Regarding the subject area of the licenses, most of these licenses which generate large revenues are pharmaceuticals (e.g. drug Taxol for Florida State University) or broadly adopted biotechnology tools (e.g. recombinant DNA patent at Stanford University). It has also been estimated that 60 to 75 percent of the university licenses are related to life sciences while another 10 to 20 percent are from electronics/software/IT fields (Roessner, 2013). About 10% of the licenses go to start-ups, which many RASOCs are classified as and are fully dependent on the license transferred(Thomas, 2007).

The lag between licenses and eventual commercialization vary widely because of the nature of the licenses as well as the regulatory process in later-stage development processes. Therefore, only less than half of the startups would obtain enough funding to bring the technology to the market. Because of the faster transfer process in RASOCs, some studies suggested that RASOCs actually generate more financial returns than licenses to large or small companies (Siegel, 2007).

III.Theoretical Development

University Production Function

Most studies of university production function treat R&D expenditures as an input variable while using different out variables. Patent statistics have been used as indicators of research output from private firms in previous studies. However, some research of university production functions used the number of publications from the research as the output. However, using the publications present some empirical difficulties, including the availability of the comprehensive data, how to account for the fluctuating number of academic journals and how to measure spillover effect from other science fields.

Coupe (2003) estimated the university patent production function as a function of R&D expenditures and, in some specifications, number of Public/R&D staff or staff. Coupe used Poisson and negative binomial models to estimate the patent production and found decreasing returns to scale after controlling for institutional fixed effects. In addition, he found that Bayh-Dole Act did not have a significant effect on patenting activity but the establishment of TTOs does, perhaps as a direct result of the Bayh-Dole Act.

Foltz (2007) described university's production output to be a combination of doctorates, patents and publications. Between these outputs, the study found evidences for an economy of scope between patents and publications but a negative association between doctorates and patent or publication production. Examining the link between publication and patent in a global context, Wong (2009) found that between 1977-2000 universities patents grew faster outside of US than in the US. In addition, Wong found that internationalization of faculty members reduced the patenting by North American universities.

While licenses of technology does not equal to patents, they share similar traits as measureable metrics for university output as a result of the research. Furthermore, because of its position further down the value chain of university, it more precisely reflects the projects that have the high potential to become commercialized. While all patent filing is required to be "useful", not all patents can be commercialized because of various factors such as market conditions or practical constraints. Therefore, licenses more closely associate with the societal welfare the university generated than patents do. This study does not aim to measure doctorate as a measurable output as it has been found that there exist a tradeoff between patent and doctorate production; research expenditures may have high effect on patents than doctorate productions.

However, using the licensing income as university output can also be biased. In the majority of institutions, most of the licensing income came from one or two high-earning licenses while the rest do not contribute significantly to the income (Thomas, 2007). Therefore, it may not be the perfect measure for university's licensing activity. To more precisely reflect the university output in transfer the technology developed, I hypothesized the following model

- The number of licenses carried out by universities in a set year is determined by
  - Total stock of knowledge the university possess, as measured by the past research expenditures from Federal government or Industrial funding sources
  - The ability of the University TTO, as measured by the experience of TTO and the number of TTO full-time licensing employees (excluding non-licensing supporting staff)
  - The University characteristics that directly influence the type of research conducted in the university such as land grant status, having a medical school and the control of the university (public or private).
- In addition, the research expenditures are determined by
  - The absolute size of the university
  - The general level of research activity in the institution
  - Environmental variables that do not directly affect technology licensing: religious affiliation and the size of endowment

In summary, the total number of licenses is determined by past research expenditures, TTO characteristics, and university characteristics. Research expenditures are determined by the set of university characteristics that do not directly determine licensing activities.

Previous studies have outlined the production function of the university and the intellectual property produced. Particularly, the licensing activity has been focused on using either licensing income or licensing income as a percentage of the total university research expenditure (Heisey, 2009). While licensing income is continuous and can be more informative about the relative weight of different licenses, licensing activity may not accurately the licensing activity for year t as some licenses provide running royalties across multiple years. In addition, most of the institutions have only one or two licenses that dominate the majority of its licensing income every year (Thomas, 2007). Therefore, it is inadequate to use only licensing income as the university output as most of the licenses do not directly contribute to the licensing income immediately unless the licenses are executed under a lump sum royalty scheme. In this study, I first attempt to use the number of licenses executed every year as dependent variable. While using the number of total licenses executed provide no information about the differences exist among licenses, the total number of licenses executed can still be a significant measure as university output.

IV. Data

A. Licensing activity

We used the data from both the annual Licensing survey from the Association of University Technology Managers (AUTM). AUTM data have been self-reported by TTO licensing officers and normally received replies from over 80% of its members and about

150 institutions annually, which covers the majority of American research-oriented universities. AUTM respondents' research expenditures represent more than half of the total federal supported research expenditures every year.

The survey asked the institution's annual total royalties income from licenses and options that generate more than $1000 USD income and the number of US patents filed between 2000 and 2011. The licenses may be exclusive or non-exclusive grant of the use of technology while options are defined as licenses with an finite exclusive period. In addition, the AUTM survey asks institutions to self-report total, federal and industrial research expenditures as well as other TTO information like disclosure data. TTO related metrics are also incorporated into the survey such as the year of establishment for TTO office when the offices have at least 0.5 full-time employees (FTEs). The experiences of TTO are estimated by the total year TTO has been in operation (current year – year TTO established). The number of licensing TTO employees are also reported while excluding supporting staff that is not related to licensing activity. It is worth noting that 60-75% of the licensing income to universities are in life science related field and 15-20 percent is in software and IT , according to AUTM survey respondents (Roessner, 2013). In AUTM survey, the universities self-reported name sometimes changed overtime. For instance, Ohio State University and The Ohio State Research Foundation were both used in

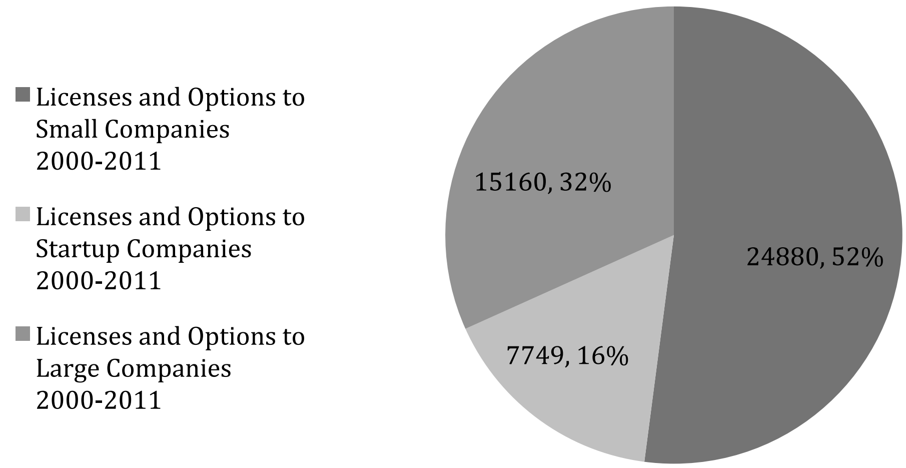

Figure 2. Licenses and Options to Type of Companies 2010-2011
Source: AUTM survey

different years.

The institution unit we used in the data depend on the reporting units to the AUTM survey i.e. whether they respond as a single-campus university or as university system. The data from other surveys are merged by name of institutions; if the data are reported in AUTM as university system but individual universities in other datasets, the data are cleaned to match to the AUTM observations by aggregating individual campus observations (e.g University of California System). In addition, for institutions that report in the name of non-profit research foundation (e.g. Ohio State Research Foundation), I matched the referred institution to the name of institutions represented by the Federal Interagency Committee on Education (FICE) code. 52 % the licenses in the survey partner with small companies with fewer than 500 full-time employees. 16% of the licenses and options partner with a new startup that are established on the base of license/options negotiated (Figure 2).

Table 1. Summary Statistics for R&D Expenditures reported to NSF Survey of Research and Development expenditures at Universities and Colleges (academic R&D expenditures survey) 2000-2011

	Federal funded Higher Education R&D Expenditures (thousands USD$)				Industry funded Higher Education R&D Expenditures (thousands USD$)			
Year	Mean	Standard Deviation	Max	Min	Mean	Standard Deviaiton	Max	Min
2000	105257	152825	1415227	378	13086	21470	177664	0
2001	109675	162972	1494839	371	12544	20739	171903	18
2002	118743	176196	1635932	456	11721	19142	165357	0
2003	125383	190392	1823191	474	11128	19474	162712	0
2004	135385	207291	1990940	592	10439	18089	155527	0
2005	138242	210096	2030009	455	11201	19797	157444	0
2006	137640	207847	2001502	289	11226	20110	162879	0
2007	138177	203472	1962625	205	12326	23614	185035	0
2008	138999	204048	1935404	332	13030	24451	213493	0
2009	141287	215622	1970091	474	13474	28485	262043	0
2010	160437	238046	2161111	389	13500	29419	264659	0
2011	153595	181952	1472874	484	11114	18504	169033	0

B. Research and Development Expenditures Statistics

The R&D expenditures of different institutions from are collected by the source of funding. The monetary figures from both sources are deflated by the fiscal year GDP based on 2000 as of May 2009).

From the National Science Foundation's Survey of Research and Development Expenditures at Universities and Colleges (academic R&D expenditures survey). The academic R&D expenditures survey includes R&D expenditures variables from different source of funds (federal, state and local, industry, institutional and other), recipient structures (passed from recipient or subrecipient), expenditures in Science and Engineering (S&E) fields. From 2003, the academic R&D expenditure survey also collected the number of Principal Investigators and Postdoctoral in each institution. In addition, the AUTM data provide self-reported research expenditure figures. The NSF survey data is merged to AUTM data set and all schools that did not respond to AUTM surveys are skipped without the information on licensing activities. Analysis has been done to both sets of expenditures with similar results.

Results presented in this paper use the NSF figures because of the comprehensive nature of NSF survey. The AUTM survey includes expenditures from two sources (Federal and Industrial), while NSF survey included two other sources of expenditure (Institutional and Other). Since the majority of research expenditures in higher education came from the sum of federal and industrial expenditures, I examined the Federal and Industrial funding from both data sets and obtained similar results.

C. University Characteristics

Data about particular institutions are gathered from a variety of sources as stated on *Table 3*. These characteristics provide us with a picture about each institution. 60-75 % of the university licenses are based in life sciences while other 10-20% of the licenses are related to software/IT/electronics (Roessner, 2013). Since institutions with medical school are more capable in medical research, the presence of medical school can have positive effect on the number of licenses executed. Similarly, land grant institutions were designated with the mission to conduct practical agricultural studies and engineering research while have a larger economies of scale and scope in research, which can also determine the type of research and number of licenses executed (Foltz, 2007).

The characteristics and performances of TTOs have been studied extensively and most studies found positive associations between the size and experience of TTOs and both licensing revenue and numbers, but not the licensing efficiency, which is normally calculated by dividing licensing income by total research expenditures (Heisey, 2009). From qualitative analysis from interviews, Siegal (2003) found positive correlation between number of TTO staff and number of licenses executed

Table 2 Summary of Institutional characteristics

Variables X^n	Description	Source
SOM	If the school has a school of medicine	Association of University Technology Managers (AUTM) Licensing Survey
Special Focus	If the school only focus on one single discipline (e.g. independent schools of medicines)	Carnegie Foundation for the Advancement of Teaching
Religion	If the university is affiliated with Association of Catholic Colleges and Universities, Council of Christian Colleges & Universities, Church of Latter-day Saints or General Board of Higher Education & Ministry (United Methodist Church)	associations of colleges or churches
LandGrant	If the school is a land grant school	Association of Public and Land-Grant Universities
Public	=1 if the institution is mostly public	National Science Foundation Academic R&D Expenditures Survey
Large, Medium, Small	=1 if the school is 1very small (<1000 undergraduate and graduate enrollment), small (1000-2999), or Large (3000-9999)	Carnegie Foundation for the Advancement of Teaching
TTO FTEs	The number of full-time employees for the institution	AUTM Licensing Survey
TTO experience	Experience of TTOs, proxy by the length of the existence of the TTO	AUTM Licensing Survey
Res_rating_h/vh	=1 if the schools is of 1 very high research activity 2 high research activity 3 doctoral research universities	Carnegie Foundation for the Advancement of Teaching
Log (endowment)	Ten Log of the size of university endowment in constant USD	Center for Measuring University Performance

but not licensing income. Siegal also found other environmental variables, such as external legal fee and number of disclosures conducted to be positively associated with licensing income, but not the number of licenses. However, because of the high correlation between most TTO characteristics, we used both the size to TTO's licensing staff and the years in existence of TTO as control variables for measuring TTO.

Some other environmental variables, such as religion affiliations and size of endowments, do not directly determine the licensing activites but may be correlated with research expenditures are also recorded.

The combined dataset of AUTM licensing survey and NSF Survey of Research and Development Expenditures at Universities and Colleges presents unique advantages. First, the panel structure allows the analysis of past research expenditures on

IV. Empirical Specifications

We incorporated the polynomial distributed lag models (PDL) in order to accurately measure coefficients of the lagged variables.

To determine appropriate instrumental variable for research expenditures, we first estimated the research expenditures using year-fixed effect OLS. I estimated the research expenditure as the function of time-variant and time-invariant university characteristics as follows:

$$(Log(ReschExps.)) = \sum_{v=0}^{n} \beta_v X_{it} + \sum_{k=0}^{n} \sigma_k Z_{it} + \delta_t + \mu_{it} \quad (1)$$

in which the research expenditures of institution i in year t is determined by a set of time-variants university co-variates X and time invariant dummy variables Z with a year-fixed effects for year t δ and a normally distributed error term μ.

I also estimated the effect of finite distributed lags and covariates on the log of the total number licenses. Just like a standard OLS model, the basic model of PDL is described below

$$(Log(licensesexec_{it})) = \sum_{v=0}^{n} \alpha_{1j} (LogResearchExps.)_{it-j} + \sum_{k=0}^{n} \gamma_k P_{it} + \varepsilon_{it} \quad (2)$$

in which the log of number of licenses executed is regressed on lags of the predicted research expenditures from equation (1) with lag length n and other TTO- and School-related covariates vector P with an error term ε.

However, simple OLS will not produce unbiased α as there exist significant multicollinearity between different lags as they are all highly correlated with each other. The standard error from OLS estimation, as a result, would be large and produce statistically insignificant results and imprecise estimated α.

Past literatures have employed a structured low-degree PDL (Almon Lags) to deal with the multicollinearity in which we assume there exist a polynomial distributed relationship between different lag weights α. For this study, we used second-degree polynomial models as follows:

$$\alpha_{1j} = \lambda_0 + \lambda_1 j + \lambda_2 j^2, j = 0, 1, 2, \ldots n \quad (3)$$

$$(Log(licensesexec_{it})) = \sum_{v=0}^{n} (\lambda_0 + \lambda_1 j + \lambda_2 j^2)(LogResearchExps.)_{it-j} + \sum_{k=0}^{n} \gamma_k P_{it} + \varepsilon_{it} \quad (4)$$

Substituting equation 3 into equation 2, we obtained the reduced form equation 4: The model allows reasonable flexibility of coefficients while assuming a secondary polynomial structure of α coefficients in equation 3. I also set lag constraint to zero in the far end (high lags) as the effect of research expenditures are predicted to decline in the long lags.

There is currently no standard way to choose the exact finite lag length *n* to use. Some studies have used high R square as standard (Alene, 2009) while Akaike Information Criterion (AIC) has also been used to measure the fit of PDL models. In the study, we tested different lag lengths and found that lag length between 4 and 5 generally maximizes adjusted R square. Another additional consideration when picking lag length is as the lag length increased in an unbalanced panel data, the number of schools and observations decreased. Therefore, I also avoid using any long lag length that reduces the number of observations to lower than 500, even if they have higher R square. The sum of all lag coefficients also represent the long-term dynamic effect of research expenditures on number of licenses executed. The polynomial coefficients λ do not inherently have economic interpretations and must be interpreted within the context of the α coefficients estimated. The estimation procedure for PDL is parallel to an OLD regression with polynomial constraints that minimized standard errors. In the 2SLS model, I used the instrumental variable to try to eliminate the endogeneity of research expenditures in PDL. The PDL models are estimated using least squares and robust Huber-White standard errors & covariance in EViews 7.2. Year-fixed effect OLS regressions are estimated in Stata 12. The results from both softwares are cross-referenced with SAS system to detect any errors.

V. Results

A. Identification of appropriate instrument for research expenditures

To identify appropriate instrument variable for research expenditures, I analyzed the variables related to university characteristics to the federal and industrial expenditures (Table 3). The discrepancy in estimated coefficients between the AUTM Licensing survey and NSF academic R&D expenditures survey is due to the different set of schools included. There exist substantial similarity in the significances of the variables and signs of coefficients. Interestingly, the coefficient estimate for the interaction term between research university with very high research activity are not only positive but also larger in industrial funding than federal funding, which may indicates the industry's preference in funding for large, research intensive university relative to smaller ones or those without extensive research activities. The result also supports that larger universities have the economies of scale and scope to attract more funding from both the federal government and the industry. In addition, the religion coefficient is negative in both data sets for federal research expenditures, which may reflect the teaching-oriented nature of some

Table 3 Research Expenditure as a function of university characteristics

	AUTM Self-Reported expenditures Data		NSF academic R&D expenditures survey	
	(1) Federal Research Expenditure	(2) Industrial Research Expenditure	(3) Federal Research Expenditure	(4) Industrial Research Expenditure
Research University – Very High (RUVH) Activity	0.270*	-0.0898	0.136	-0.588
	(2.50)	(-0.53)	(0.47)	(-1.56)
Research University-High Activity (RUH)	0.0113	-0.202***	0.350***	-0.289*
	(0.30)	(-3.51)	(3.55)	(-2.15)
RUVH_Large	0.261*	0.525**	1.358***	1.499***
	(2.30)	(2.98)	(4.51)	(3.78)
RUVH_Medium	-0.213	-0.156	0.181	0.0128
	(-1.79)	(-0.85)	(0.57)	(0.03)
religion	-0.182***	0.0900	-0.593***	-0.130
	(-3.31)	(1.09)	(-4.17)	(-0.70)
accu	-0.200**	-0.423***	-0.387*	-0.929***
	(-2.87)	(-4.04)	(-2.17)	(-3.98)
logendow	0.404***	0.323***	1.013***	0.880***
	(22.74)	(12.03)	(21.52)	(14.18)
Large	-0.405***	-0.337**	-1.397***	-1.151***
	(-4.90)	(-2.71)	(-6.35)	(-3.96)
medium	-0.294***	-0.0834	-0.940***	-0.601*
	(-3.49)	(-0.66)	(-4.20)	(-2.04)
small	0.0820	0.0323	0.107	-0.388
	(0.98)	(0.26)	(0.48)	(-1.34)
Constant	5.814***	5.246***	5.905***	4.388***
	(49.16)	(29.47)	(18.77)	(10.61)
N	1509	1482	1557	1537

religiously affiliated colleges and the tradeoff between religion and research in a university's output decision.

The size of university's endowment (logendow) appear to be an ideal instrument as it is not only significantly correlate with research expenditures but also not directly related to the licensing activities in an institution. Logendow also explains at least 25% of the variation (R^2=0.2631, NSF data; 0.2527, AUTM data) in industrial funded research expenditures and at least 40% of the variation in federal funded expenditures R^2=0.4097, NSF data; 0.4335, AUTM data). Therefore, I chose logendow to be used as the instrument in 2SLS regressions in the PDL models.

B. Interaction between R&D Expenditures and Number of Licenses

To examine the interaction between research expenditures and number of licenses and options ("licenses"), we used both standard PDL procedure and PDL with 2SLS (regression 8 and 12) as shown in Table 4. Table 4 showed the effect of the research expenditures on the total licenses executed by institutions per year. Several institutional characteristics such as land grant, public and TTO experiences were included in the analysis as time-invariant covariates. We applied the model with definite lag lengths (*n*) from 4 to 8 and found similar results; results from n=5 and 7 are shown in Table 4. Comparing the p-values with different degrees of polynomials, we found in all regression the coefficients for polynomials equation become insignificant around cubic polynomial coefficients. Therefore, I used second-degree polynomial distributed lag model for the following regressions in table 4 and 5.

Among the time-variant variables that play a statistically role in determining the number of licenses executed, we found that the variables directly related to TTOs have been consistently positive. We found that both TTO experiences and the licensing staff size have been associated with licensing activity. Specifically, the addition of 1 more licensing staff are correlated with about 3 % increase in the number of licenses while 1 year of additional experiences of TTO are associated with 1-2% increase in number of licenses executed. Our findings in TTO variables are largely consistent with previous literatures that increasing staff size in TTO are associated with increasing numbers of licenses and licensing revenues (Heisey, 2007). However, to detect the endogeneity of TTO-related variables, I estimated regression 5 and 9 without TTO related variables. We observed identical signs and similar significant coefficients in regression 5 and 9 compare to regression 6 and 10 with TTO-related variables.

TTO-related characteristics are consistently positive correlated with licenses executed in all models in a significant fashion. However, the direction of causality can be both ways for number of TTO licensing employees as higher number of licenses generally leads to more hire for licensing personnel. Public schools also have significantly more licenses executed every year than private schools in all four models.

Comparing the length of significant lag variables, I found significant effect of 2^{nd} and 3^{rd} lags of research expenditures in most regressions indicating the lag length to be between 2-3 years. This corresponds to the typical modal lag for 2 years for university research expenditure in other similar studies (Heisey, 2009). Oehmke and Schimmelpfennig (2004) also found that aggregate research expenditures have significant 1 or 2 years short-term effects on US agricultural multifactor productivity. Our results indicate that it is likely that research expenditures directly impact licensing activity in short-run within two to three years. Furthermore, industrial research expenditures also have significant coefficients on 1st lags variables, indicating that time it take from expenditures to commercialization may spread wider for industrial than federal funded research expenditures.

In addition, the sum of the coefficients of lagged variables produced the long-term dynamic effect of research expenditure on percentage of licenses executed every year. Even though there exist high correlation between lagged variables (R square=0.99 for 1st and 2nd lagged NSF federal research expenditure) and PDL may not resolve the multicollinearity entirely, the linear combinations of these estimators (sum) are still generally well-estimated (Blume-Kohout, 2012). Even if the exact estimate may still different, we found a slightly higher effect of federal funded research expenditures to number of licenses than industrial funded research expenditures in identical specifications. The result does not support the hypothesis that industrial funded research tends to focus in the area with the potential to generate high amount of licenses or funding from industry facilitate the commercialization of technology. A 1% increase in federal funded research expenditures leads to higher percentage increase of number of licenses than industrial funding.

However, it is worth noting that the numbers of licenses executed do not represent the whole picture of licensing activity. Therefore, I investigated the differences in license with different type of private corporate partners, defined by their size and if the partner is a startup as shown in Table 5.

Table 4 Effect of Federal and Industrial Research Expenditures on Number of Licenses Executed								
	Federal Research Expenditures				Industrial Research Expenditures			
	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Method		OLS		2SLS		OLS		2SLS
Research	-0.08	0.0869	-0.057	0.143	0.155*	0.090	0.106	0.143
Expenditure	(-0.343)	(0.649)	(0.229)	(0.647)	(1.87)	(1.27)	(1.52)	(0.64)
1^{st} Lag	0.065	0.098*	0.0137	0.171	0.131***	0.086***	0.090*	0.171
	(0.79)	(2.19)	(0.116)	(1.52)	(4.25)	(3.19)	(2.40)	(1.52)
2^{nd} Lag	0.157***	0.0989***	0.0667*	0.179***	0.106***	0.078***	0.073***	0.178***
	(5.429)	(4.972)	(2.05)	(5.20)	(10.09)	(7.67)	(5.60)	(5.19)
3^{rd} Lag	0.200*	0.0896	0.100**	0.165***	0.081*	0.065*	0.058***	0.165***
	(2.23)	(1.637)	(2.709)	(6.85)	(2.75)	(2.55)	(5.12)	(6.85)
4^{th} Lag	0.184	0.0700	0.116	0.130**	0.054	0.048	0.0445*	0.131**
	(1.76)	(1.104)	(1.53)	(2.990)	(1.56)	(1.59)	(2.04)	(2.99)
5^{th} Lag	0.118	0.0401	0.114	0.076*	0.027	0.026	0.032	0.076*
	(1.58)	(0.888)	(1.24)	(2.089)	(1.10)	(1.20)	(1.20)	(2.08)
6^{th} Lag			0.094				0.02	
			(1.107)				(0.815)	
7^{th} Lag			0.056				0.009	
			(1.03)				(0.60)	
School of	-0.135	-0.181*	-0.299*	-0.000264	-0.007	-0.08	-0.21*	-2.65E-05
Medicine	(-1.17)	(-2.237)	(-2.47)	(-0.000137)	(-0.08)	(-1.07)	(-2.19)	(-0.00032)
Land Grant	0.098	-0.0466	-0.081	0.129	0.118	-0.053	-0.068	0129
	(1.21)	(-0.5848)	(-0.84)	(1.546)	(1.34)	(-0.62)	(-0.637)	(1.54)
Public	0.063	0.085	0.085**	0.474***	-0.138	-0.058	-0.087	0.475***
	(0.849)	(1.06)	(0.94)	(5.15)	(-1.80)	(-0.77)	(-0.93)	(5.15)
Special	-0.238*	-0.121	-0.21	0.453***	-0.293*	-0.154	-0.239	0.453***
Focus	(-2.15)	(-1.06)	(-1.50)	(3.58)	(-2.56)	(-1.45)	(-1.66)	(3.59)
TTO		0.0133***	0.009*	0.0169***		0.0156***	0.0106**	0.016***
Experience		(4.73)	(2.21)	(4.63)		(5.07)	(3.06)	(4.63)
TTO FTEs		0.038***	0.04***	0.0349***		0.041***	0.040***	0.034***
		(7.91)	(4.04)	(4.97)		(4.84)	(4.35)	(4.97)
Constant	-4.54	-3.26***	-3.28***	-4.28***	-2.11***	-1.23***	-1.36**	-4.28
	(-1.17)	(8.69)	(-3.34)	(-8.80)	(-5.76)	(-3.40)	(-2.94)	(-8.80)
AIC	2.77	2.64	2.70		2.84	2.70	2.74	
R Square	0.386	0.4546	0.421	0.4552	0.334	0.417	0.403	0.455
Sum of lagged Coefficients	0.640***	0.484***	0.505***	0.864***	0.556***	0.393***	0.434***	0.864***
N	856	849	572	689	846	841	566	689
Number of School	150	149	137	139	148	147	137	139

t statistics in parenthese * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The differences in effects from research expenditures on licenses that are executed with 1) start-up 2) small 3) large companies and 4) licenses that yielded more than 1 million in licenses in the fiscal year are also estimated as shown in shown in table 5. While sums of lagged coefficients are still higher from federal research expenditures in licenses to startup and small companies, the industry funded research have higher effect in licenses to large companies and the licenses generating more than 1 million dollar income.
Since most of the industry-sponsored research agreements requires the transfer of intellectual property to the funders, the result is consistent with the fact that most of the companies involved in sponsoring academic research are large companies. Federal government sponsored research are more likely to be commercialized with small and startup companies while industrial funded research are more likely to partner with large companies. In addition, the higher sum of lag variables in licenses over 1 million category indicated that the industry funded research projects are more likely to generate high income than federal funded research. The result confirmed that the industry funded research expenditures are more likely to generate high licensing income than federal funded research.

Table 5 Research Expenditure Sources Effects by Different Types of Licenses								
	Federal Government				Industrial Sources			
Types of Licenses	Startup	Small	Large	>1M	Startup	Small	Large	>1M
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Research Expenditure	-0.0411	-0.0095	-0.124	0.087	0.108*	0.109	0.048	-0.032
	(-0.30)	(-0.04)	(-0.57)	(0.61)	(2.44)	(1.38)	(0.67)	(-0.91)
1st lag	0.029	0.057	0.011	0.036	0.072***	0.078*	0.070*	0.007
	(0.65)	(0.74)	(0.16)	(0.79)	(4.38)	(2.67)	(2.59)	(0.47)
2nd lag	0.075***	0.097***	0.101***	0.0038	0.042***	0.051***	0.081***	0.037***
	(3.61)	(3.41)	(3.56)	(0.02)	(5.72)	(4.26)	(8.51)	(3.47)
3rd lag	0.095*	0.111	0.145*	-0.02	0.020	0.031	0.079***	0.052*
	(1.70)	(1.33)	(1.75)	(-0.35)	(1.20)	(1.04)	(3.10)	(2.53)
4th lag	0.088	0.100	0.143	-0.028	0.006	0.015	0.065*	0.050*
	(1.38)	(1.01)	(1.469)	(-0.41)	(0.317)	(0.440)	(2.14)	(2.24)
5th lag	0.057	0.063	0.095	-0.021	-0.001	0.005	0.039*	0.033*
	(1.25)	(0.89)	(1.35)	(-0.43)	(-0.04)	(0.199)	(1.77)	(2.11)
School of Medicine	-0.114	-0.209	-0.153	0.0064	-0.024	-0.090	-0.089	0.043
	(-1.55)	(-2.04)	(-1.48)	(-0.08)	(-0.365)	(-1.00)	(-1.06)	(0.54)
Land Grant	0.25***	0.087*	-0.374***	-0.23*	-0.295***	0.100	-0.436***	-0.277**
	(-3.60)	(0.98)	(-4.36)	(-2.68)	(-4.09)	(1.01)	(-5.04)	(-3.06)
Public	0.188*	0.193*	0.125	-0.060	0.114	0.050	0.047	-0.067
	(2.73)	(2.32)	(1.53)	(-0.77)	(1.66)	(0.565)	(0.569)	(-0.94)
TTO Experiences	0.005	0.0119**	0.0127***	0.010***	0.0066**	0.0146***	0.0144***	0.010***
	(1.89)	(3.02)	(4.48)	(3.99)	(2.54)	(3.89)	(5.53)	(3.93)
TTO FTEs	0.029***	0.032***	0.0466***	0.034***	0.031***	0.0366***	0.045***	0.031***
	(6.05)	(3.35)	(6.01)	(7.66)	(6.56)	(3.79)	(6.20)	(7.32)
Special Focus	-0.609***	-0.12*	-0.1048	0.342**	-0.635***	-0.151	-0.135	0.300
	(-6.91)	(-0.90)	(-0.99)	(3.02)	(-7.06)	(-1.06)	(-1.34)	(2.60)
Constant	-2.27***	-3.04***	-2.86***	-0.522	-1.05***	-0.896*	-1.996***	-1.16***
	(-4.85)	(-4.28)	(-3.92)	(-1.19)	(-4.46)	(-2.25)	(-5.98)	(-3.41)
AIC	2.249	2.88	2.67	1.64	2.26	2.95	2.64	1.60
R Square	0.3430	0.326	0.394	0.382	0.334	0.285	0.413	0.408
Sum of Lagged Coefficients	0.3042***	0.419***	0.373***	0.0528*	0.249***	0.291***	0.383***	0.140***
N	711	774	720	349	705	766	713	345
Number of Schools	142	147	142	78	142	145	141	78

t statistics in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

VI. Conclusion

We found evidences that federal government funded research led to a higher percentage of number of technologies been licensed from universities between the year 2000 to 2011. Before the passage of Bayh-Dole Act, studies found that the federal-funded research were not fully commercialized and thus require incentives for academic inventors to commercialize the research (Cardoza, 2010). The results show that the gap in commercialization seems to disappear in terms of the number of licenses generate by federal and industry supported research. There also exist little differences in the time between lab benches and technology transfer for federal and industry funded research, which takes about 2-3 years.

However, there still exist a difference in licenses arising from federal and industrial funded research expenditures. Industry funded research projects are more likely to result in partnering with large companies and generate large income per licenses while federal funded research projects partners with small and startup companies. For policy makers, the study indicated that the biggest beneficiary from federal funded research and its technology transfer are small companies and startup while large companies are equally benefited from federal and industrial funding. The lower impact of federal funded research projects on licenses generating over 1 million dollars in licensing income requires additional studies in understanding if the differences are entirely due to federal government supports lower commercialization potential projects.

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