Econometrics Project Help

Sample Assignment

Topic:"The regional economy of Louisiana is positively influenced by technology transfer" Where technology transfer results in a combination of many other variables, that you will be able to see in the dataset, such as patents, start ups, licenses, research expenditures and so on. Obviously, you will have to choose for the best suited econometric technique, checking for endogeneity, multicollinearity, using tests etc. You have to provide also tables, graphs if any, in way which is very user-friendly.

I. Introduction

Views of the role of academic research have evolved over time. Among economists, support for public funding fora university role in basic research has a longstanding basis in the public goods argument that the benefits of basic research are too diverse for a single firm to capture, and therefore a system of private markets will supply less basic research than is socially desirable. More recently, Aghion, Dewatripont and Stein (2005) have indicated that even if perfect property rights protection were available, the university setting is well-suited to basic research.They arguethat an academic researcher's freedom to pursue projects of their choice implies a higher, compensating wage for private sector researchers (whose research interests and projects are imposed) that flips the sign of expected payoffs from research projects with high but risky potential payoffs from positive in an academic setting to negative in a private sector setting. Their conclusion is especially powerful when commercial application of research is at the end of a sequence of research projects, with success at later stages depending on success at earlier stages, because after successes in early stages the remainingresearch becomes less risky and hence profitable for private sector businesses. Arora and Ceccagnoli (2006)providea rationale for university licensing of patents at the later stages of research by observing that production is more profitable relative to licensing when the knowledge-holder holds complementary assets, namely marketing and production expertise, which universities frequently lack.[1]

1The simple observation that research performed at a university is less expensive than research performed in the private sector motivates industrial funding of university research, and the AUTM survey reports that Louisiana universities received more than $56 million in research funds from industry in 2013. But it also raises the question of why private companies simply don't fund all research through universities. Aghion, Dewatripont and Stein (2005) answer this by noting that the reason for the lower wages received by academics is freedom from an imposed research agenda. Arora and Ceccagnoli (2006) supplement this rationale with the observation that final

In the policy arena, the Bayh-Dole Act of 1980 has encouraged a greater degree of collaboration between universities and business firms in transferring technology from academic institutions to the private sector. Prior to passage of the Bayh-Dole Act, patents for inventions that were developed as the result of federal grants were assigned to the federal government. Under the Bayh-Dole Act, small businesses and non-profit organizations such as universities are permitted to retain patent rights from inventions developed with federal funds. Armed with patents or even without patents but at least holding intellectual property rights that are not subordinate to the government's, universities are free to license new technologies they have developed to private businesses.

According to an annual survey undertaken by the Association of University Technolohgy Managers (AUTM), universities in the State of Louisiana earned more than $24 million in licenses fees alone in 2013. But not only has the Bayh-Dole Act been profitable for universities through license agreements, O'Shea, et al. (2005) report AUTMestimates that startup companies from academic institutions were responsible for 280,000 jobs in the US economy from 1980 through 1999, and that as of 1997, annual sales of startups orginating from MIT alone were $232 billion annually. Indeed, O'Shea, et al. (2005) suggest an evolving "third role" for universities in regional economic development from generating startups and developing commercially useful inventions in addition to the traditional missions of research and knowledge dissemination to academic and student communities and prepation of students to contribute to firms and society.

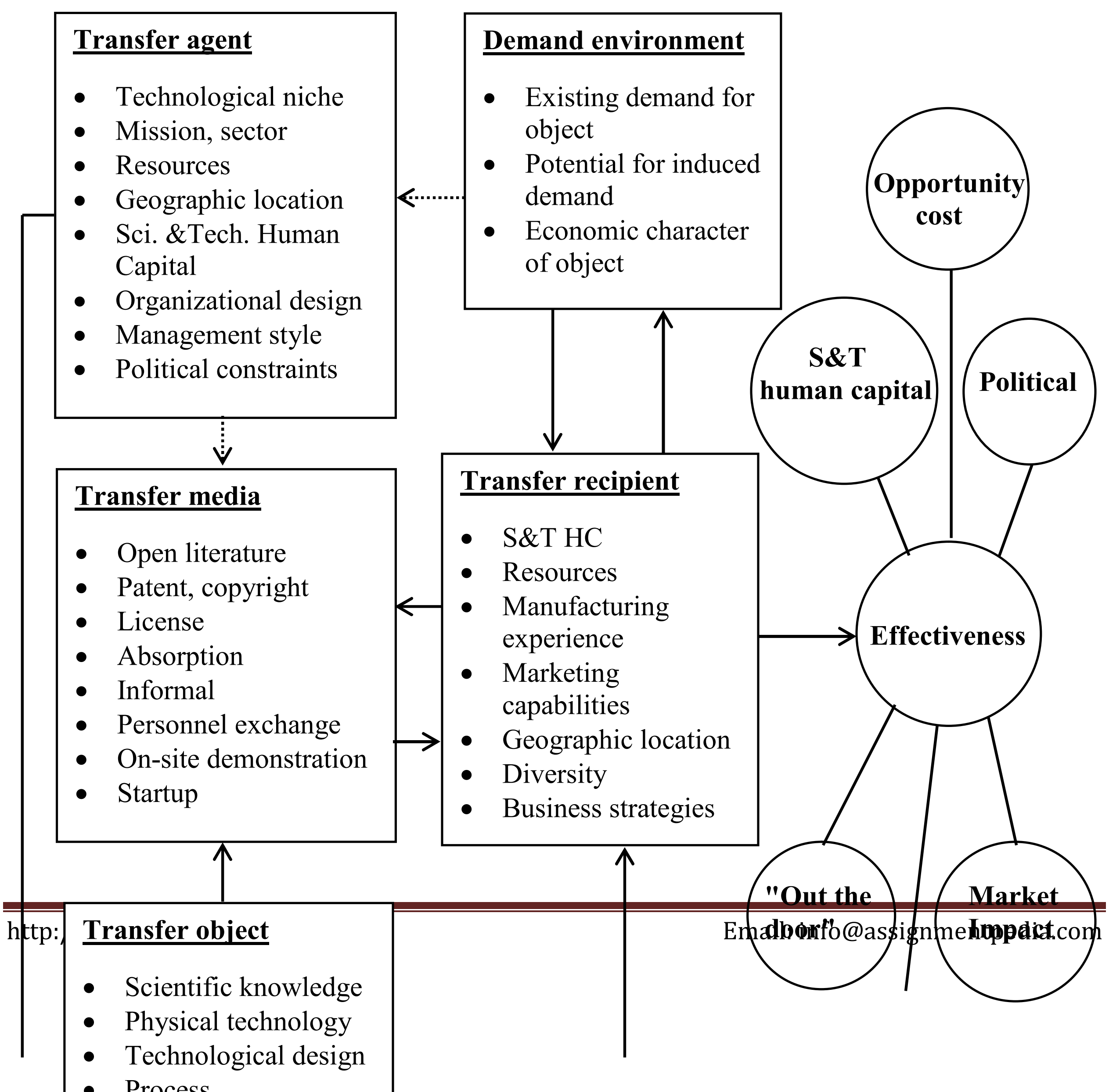
In this paper, data from annual AUTM surveys of universities in Louisiana is used to develop a simultaneous equations model of research outputs in those universities. Specifically, outputs of inventions, patents, licenses, license revenues and startups are modeled as functions of several different inputs tracked in the data set. The paper is organized as follows: Section II provides an overview of the literature on university technology transfer and draws implications from that literature; Section III discusses the data and econometric model; Section IV discusses results of estimation and Section V briefly summarizes and discusses results.

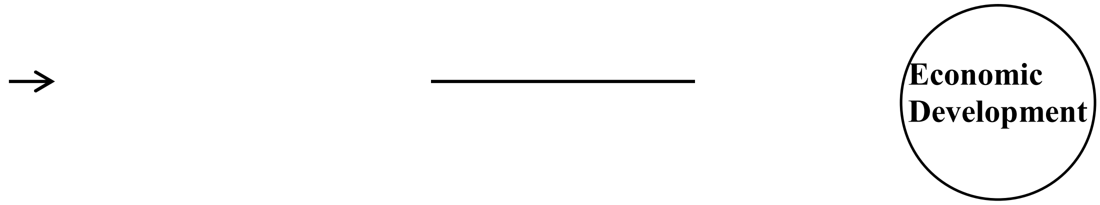
II. Background Literature

commercialization of research is more valuable in a setting in which complementary marketing and production assets reside.

To organize a review of the literature on the effectiveness of technology transfer, Bozeman (2000) provides the conceptual diagram recreated below as Figure 1, which detailsfive important dimensions of the technology transfer process, Transfer agent, Transfer recipient, Demand environment, Transfer media and Transfer object, or as Bozeman describes them "who is doing the transfer, how they are doing it, what is being transferred, and to whom" (p. 637). The transfer agent is taken as the university, including its technology transfer office (TTO), and research community which of course includes additional agents. Within the transfer agent are embedded a host of important factors including the university's mission, geographic location, any

Figure 1 *Contingent effectiveness model of technology transfer*





(Source: Bozeman (2000))

scientific and technical expertise specific to the university such as inclusion of a medical school or special centers associated with regional economic components (fisheries, agriculture and so forth). Design elements include whether the technology transfer office is decentralized, with different units for different departments or centralized into a single unit. Management style and political constraints include such factors as the emphasis placed by various academic departments and/or the university on publishing versus patenting, licensing and technology transfer in the tenure process.

The other agent in Figure 1 is the transfer recipient, typically a private sector business. The transfer recipent has its own scientific and technical human capital. From surveys of 355 firms that participated in National Science Foundation academic institutions designated as Engineering Research CentersFeller, Feller, Ailes and Roessner (2002)find that the most important function the university serves is the combination of keeping local firms plugged-in to a cutting edge network of research techniques and knowledgeable students (corresponding to the absorption, informal, personnel exchange and on-site modes in the Transfer media category) rather than specific products and processes. From the Transfer agent's perspective, key characteristics of the Transfer recipient are its business strategy, production facilities and marketing capabilities, skills and expertise that are not usually resident among university research faculties or Technology Transfer Offices.

Several measures of effectiveness result from the interplay of Transfer agent, Transfer recipient, Transfer media, Transfer object and Demand environment. In evaluating outcomes and measuring effectiveness, one should remember that universities are not profit maximizing enterprises; rather, within the management literature, they are often viewed as bureaucracies.

Opportunity cost, in this context, measures the lab director's and scientists' preference that technology transfer, which from their perspective is often not as important as scholarly research and output, not be unduly costly to these more important outputs. Although perhaps not directly measurable as an output, Bozeman asserts that opportunity cost remains an important internal measure of effectiveness that can usefully organize thought. The simplest measure of effectiveness is "Out the door," which refers to perfunctory action in response to a mandate to make technology available to the private sector in pursuit of simple but easily measured results such as licenses and patents.[2] The Political measure of effectiveness has arisen in surveys and paints technology transfer activities as a means to an end, namely increased political support that is later manifested in renewed or increased funding from public sources or in favorable mentions of the university to policy makers. The development of scientific and technical human capital refers to the two way transfers of knowledge that occur between the university and private partners through research networks that may involve collaboration, demonstrations of technology and technology transfer through employment of university graduates. Of course, Market Impact and Economic Development are the primary aims of the Bayh-Dole Act, but they generally require detailed case studies to evaluate, with the leading empirical examples being centered on Silicon Valley-Stanford-Berkeley and Boston-Harvard-MIT.

Given the data available from the AUTM surveys, the focus here is on counting measures of effectiveness, specifically patents, licenses, startups and university revenues from licenses and turn to several relevant, more focused empirical papers.

Link and Siegel (2005)combine their own informal surveys with AUTM data to develop a stochastic frontier model of relative efficiency in producing licensesand license revenue. Their informal surveys provide three stylized facts. First, although Bayh-Dole requires university researchers working under federal grants to disclose inventions to the university TTO, they typically do not do so and universities frequently do not enforce these rules.[3] For this reason, labor input from the TTO unearthing and documenting new inventions is critical. Second,

[2]Bozeman (2000, p. 644) reports that in surveys undertaken in the 1980s and early '90s a common response to the question "what motivates your technology transfer activity"was "we were told to."

[3]One explanation is that university faculties are not provided with much incentive to pursue licensing. Most universities' promotion and tenure policies view commercial activity as less important than scholarly publication. Additionally, financial rewards to faculty from licensing are frequently under 30 percent of the license royalties generated, although this varies across universities (Link and Siegel 2005).

licensing of inventions typically occurs long before patenting, if patenting occurs at all. Finally, property rights lawyers are important inputs purchased by the university both to protect intellectual property and to negotiate and re-negotiate licenses. Findings include the following: 1, both the number of licenses and license revenues are positively related to the number of invention disclosures, 2, additional TTO staff generates more license agreements, but not additional license revenue, 3, additional spending on lawyers generates more license revenue, but not more license agreements. Macho-Stadler, Perez-Castrillo and Veugelers (2007) use a game-theoretic model of reputation to suggest that the latter finding may be the result of the university technology seller (or lawyers acting as their agents) needing to "shelve" some potentially licensable but lower quality inventions in order to maintain a repuation for quality when firms cannot diectly assess the quality of the invention as well as the university.[4]

O'Shea, et al. (2005) construct a random effects negative binomial model of the count of startups, using the AUTM surveys from 1980 to 1991 as a source of data. Of relevance to the present investigation, they find the number of startups to be increasing in the number of employees in the university's TTO as well as in the proportion of total research funding comprised of industrial sources.

Arora and Ceccagnoli (2006) investigate the decision of whether to monetize an invention via patent and license or patent alone. Although they use data from private firms rather than universities, their findings should still be relevant. They argue that the strength of patent protection, in the sense of how readily rivals can produce competing products without licensing from the patent holder, influences the decision to patent. However, stronger patent protection raises the value of patents more for firms that hold assets complementary to the patent and also raises the value of patents for own production relative to patents for licensing. In a university setting, we might expect their results to imply, for example, that the patentable products of an agricultural center will be licensed because the university lacks the scale of production to extract as much value from the patent from own production as from licensing. In contrast, new inventions from computer science departments, such as programs that provide various services,

[4]In the absence of a patent, one problem for technology sellers is how to describe the technology completely enough to convince a buyer that it is both viable and commercially significant without also providing details that would allow a buyer to imitate rather than purchase the technology.

might be more likely to be the source of startups because the complementary assets related to their use (e.g., Internet access for distribution and "buzz" about their existence from social networks) is more readily available.

Using a case study methodology, Harmon, et al. (1997) emphasize the importance of relationships between the university and the firms that would reap commercial benefit from inventions. They find that only four of 23 firms that commercialized inventions developed at the University of Minnesota from 1983 to 1993 had had no prior relationship with the University and more than half of the technologies that were transferred either upgraded existing products or extended existing product lines. One of their important conclusions is that TTO personnel do not typically act as "middlemen" between private firms shopping for technology solutions and the researchers at their institution who have those solutions at hand, which is consistent with the findings of Link and Siegel (2005). More recent research discussed by Phan and Siegel (2006) emphasizes the role of university-specific factors such as the weight (or lack thereof) placed on technology transfer in the tenure process, varying incentives for faculty provided by various license fee sharing percentages, the presence of "star" researchers and so on.

From the literature, it is clear that a variety of factors influence universities' success at technology transfer. Several factors that determine performance are university-specific. Because data on these factors is lacking, a set of binary indicator variables for universities is used in the structural model below. In addition to university-specific factors that are not observable, technology transfer depends on several variables that are included in the AUTM data including research spending by the university, the number of employees in the TTO office, and spending on legal fees to carry out patenting, licensing and new firm creation processes.

III. Data and Econometric Model

The data are from an annual series of surveys of university Technology Transfer Offices (TTO) undertaken by AUTM that were administered from 1991 to 2013. Broadly speaking, the survey covers a variety of inputs the university uses to produce new technology that can be transferred (research expenditures, TTO staffing levels, legal fees) and outputs (numbers of patent applications, license/option agreements, new startup companies, and revenues from license agreements).

The target population for the surveys is all universities in North America that conduct significant technology transfer activities. AUTM desires these surveys to be completed by all university technology transfer offices in North America, but survey response is voluntary. To encourage survey response, AUTM allows university TTOs to indicate that they would prefer that their response be anonymous, and in our sample limited to Louisiana, universities that responded anonymously account for about 30 percent (26 of 87) of all survey responses.[5]In the data set, universities that respond anonymously also have the year of their response eliminated as well as whether they have a medical school or not. Therefore although the surveys are intended to form a panel of data over time, the anonymity that universities have availed themselves of and the focus on Louisiana limits the econometric techniques available. Additionally, lack of an identifying year for some of the data means that nominal variables cannot be converted to real variables by use of a price deflator, which increased by a factor of 2.67 from 1991 to 2013.

The variables that are usedare listed and described in Table 1 below.

Table 1

Variable names and definitions

Variable	Definition
TotFTEs	Total FTEs in TTO
TotResExp	Total research expenditures, millions of current dollars
IndResExp	Industry funded research expenditures, millions of current dollars
LicGenInc	Number of licenses generating income in the survey year
LegFees	Total legal fees in survey year, millions of current dollars
InvDisRec	Disclosures of inventions received by the TTO in the survey year
GrossLicInc	Gross income from licenses
StUpsFormed	Startups formed
TotPatAppFld	Total patent applications filed
LicIss	Licenses/options issued in the survey year

Of the 87 surveys available for 1991 to 2013, 64 surveys have all of the data in Table 1. Descriptive statistics for the sample are provided in Table 2 below.

[5]Louisiana universities or centers of universities that identified themselves include Louisiana State University (LSU in the model), LSU Agricultural Center (LSU_AG), Tulane University (TULANE), the University of New Orleans (UNO) and Louisiana Tech University (LATECH). None of these has a complete time series for 1991-2013.

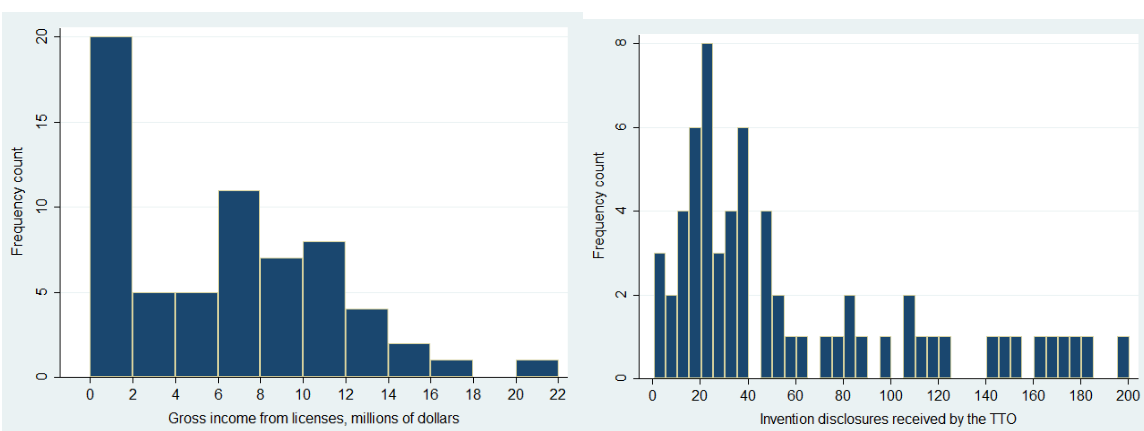
Table 2*Descriptive statistics, annual data*

	N	Mean	Std. Dev.	Min	Max	Q1	Q2	Q3
TotFTE	64	5.63	5.17	0.03	19.4	2	3.50	8.50
TotResExp	64	179.50	173.84	14.17	615.66	50.27	124.31	209.18
IndResExp	64	15.52	12.69	0.25	57.81	5.22	13.78	20.05
LegFees	64	0.63	0.79	0	4.29	0.16	0.32	0.95
LicGenInc	64	35.28	32.67	2	132	13.5	21	47
InvDisRec	64	59.27	53.21	3	196	21	36.5	86.5
GrossLicInc	64	6.19	5.13	0	20.98	0.97	6.49	9.86
StUpsFormed	64	1.88	2.19	0	8	0	1	3
TotPatAppFld	64	37.06	36.72	0	132	13	21	49
LicIss	64	8.59	8.62	0	34	1.5	6	13.5

For most of the variables in Table 2, the mean is greater than the median (Q2), which implies the distributions are positively skewed. Frequency histograms for two of the variables, *GrossLicInc* (annual gross license income in millions of dollars) and *InvDisRec* (annual invention disclosures) are depicted in Figure 1 and illustrate the skew for those variables. Looking at resources consumed, 5.63 FTEs were employed in the TTO and total research expenditures per year averaged $179.5, of which an average of $15.52 million came from industry. Additionally,

Figure 1*Frequency histograms of license income and invention disclosures*

a. Histogram of gross license income *b. Histogram of invention disclosures*



universities spent an average of $630 thousand per year on legal fees associated with technology transfer (e.g., patent filings, negotiating and writing license agreements and agreements with startups). The number of licenses generating income in the year of the survey averaged 35.28. Turning to the outputs of technology transfer, an average of 59.27 inventions were disclosed each year, average gross license income was $6.19 million per year, and on average 1.88 startups formed, 37.06 patent applications were filed and 8.59 new licenses were issued. Note that more than a quarter of the observations involve no new startups created at a university in a year.

Researchers have occasionally used single equation models to predict patents, licenses or licensing revenues, but the input variables are highly collinear with the consequence that single equation models yield imprecise estimates. Table 3 below provides pairwise correlations between fulltime TTO employees, total research expenditures, legal fees and, for example, invention disclosures received at the TTO. All of the inputs *TotResExp*, *TotFTE* and *LegFees*have pairwise correlations greater than 0.7, and all are correlated with *InvDisRec* with correlations greater than 0.73.

Table 3 *Correlations between invention disclosures, research expenditures, FTE employees and legal fees*

	InvDis	TotResExp	TotFTE	LegFees
InvDisRec	1.0			
Significance	---			
N	64			
TotResExp	0.951	1.0		
Significance	0.0000	---		
N	64	64		
TotFTE	0.973	0.971	1.0	
Significance	0.0000	0.0000	---	
N	64	64	64	
LegFees	0.735	0.751	0.702	1.0
Significance	0.0000	0.0000	0.0000	---

N	64	64	64	64

The correlations in Table 3 are part of the motivation for the simultaneous equations approach adopted here. Specifically, in the model estimated below, the resource inputs to the technology development and transfer process are research expenditures (*TotResExp*), TTO personnel (*TotFTE*), and legal fees (*LegFees*). Disclosures of inventions to the TTO (*InvDisRec*) are an intermediate product that results from research expenditures and TTO labor in obtaining information on new inventions from faculty members. The intermediate product of invention disclosures along with legal fees are related to new startups (*StUpsFormed*), patent filings (*TotPatAppFld*) and new licenses (*LicIss*). Finally, both new licenses issued which generate income and previously issued licenses that currently generate income (*LicGenInc*) are related to the gross license income (*GrossLicInc*) the university receives. Thus, as a set of simultaneous equations, we have the following system:

$$InvDisRec_{i,t} = \alpha_0 + \alpha_1 TotFTE_{i,t} + TotResExp_{i,t} + \varepsilon_{1,i,t}$$
$$LicIss_{i,t} = \beta_0 + \beta_1 InvDisRec_{i,t} + \beta_2 LegFees_{i,t} + \varepsilon_{2,i,t}$$
$$StUpsFormed_{i,t} = \gamma_0 + \gamma_1 InvDisRec_{i,t} + \gamma_2 LegFees_{i,t} + \varepsilon_{3,i,t}$$
$$TotPatAppFld_{i,t} = \delta_0 + \delta_1 InvDisRec_{i,t} + \delta_2 LegFees_{i,t} + \varepsilon_{4,i,t}$$
$$GrossLicInc_{i,t} = \theta_1 + \theta_2 LicGenInc_{i,t} + \varepsilon_{5,i,t}$$

The vector of errors ($\varepsilon_1, \varepsilon_2, \epsilon_3, \epsilon_4, \epsilon_5$) is assumed to have a zero mean for each observation *i* at all times *t*.Observe that the first four equations form a recursive system, in that new inventions disclosed, an endogenous variable,is included as a determinant of licenses, startups, and patents, but new inventions disclosed is not itself a function of any endogenous (i.e., left hand side) variables. Therefore if ($\varepsilon_1, \varepsilon_2, \epsilon_3, \epsilon_4$) were independent across all periods *t* as well as within each period for each *i*, then the first four equations could be estimated using OLS equation by equation. However, it is very likely that there are omitted variables that would lead to contemporaneous correlation among ($\varepsilon_1, \varepsilon_2, \epsilon_3, \epsilon_4$).Additionally, since current gross license income depends in part on past licensing decisions through licenses that currently generate income, there is necessarily serial correlation in gross license income and cross equation serial correlation between past licenses issued and current gross license income. Moreover, any omitted variables that are serially correlated in any equation will impart serial correlation into each of these equations.

Because the data do not contain the time dimension, serial correlation cannot be treated directly. Instead, two features of the estimation represent crude attempts to minimize the problems imparted by serial correlation. First, a binary indicator variable for each identified university is created and included in each equation in the system. Under this parameterization, all of the universities that do not identify themselves are treated as a single university and the intercept in each equation is an intercept for this group. For each university that identifies itself, the estimated coefficients on its indicator variable in each equation is an estimate of the difference between it and the group of unidentified universities. One advantage of this dummy variable treatment is that any unobservable variables that are university-specific and do not change over time are incorporated into the estimated intercept. For example, much of the research on technology transfer effectiveness includes an indicator for the presence of a medical school at the university. In the present model, as long as the medical school exists for all of a university's observations, its effects will be absorbed in the intercept estimate for the university.

Second, the system of equations is estimated using a two-step General Method of Moments (GMM) estimatorthat leads to covariance matrix estimation at the second stage that is robust against first order serial correlation and heteroskedasticity in the disturbances. So-called HAC estimation (Heteroscedasticity and Autocorrelation Consistent estimation). In the first stage estimation, all of the exogenous variables in the system, *TotResExp, LegFees, TotFTE,* and the university indicator variables, are used to obtain estimates for each of the structural equationparameters using the orthogonality condition between the residuals for each equation and the instruments. The estimated parameters from this first step are unbiased estimates of the population parameters if the structural equations themselves are correct specifications for the expected values of the endogenous variables. At the second stage, the errors from the first stage are combined with the instruments to produce a weight matrix for second stage estimation that allows for heteroskedastic errors with first order serial correlation for each equation. Therefore along with the equations given above and the implied exogeneity of *LegFees*, *TotFTE*, and

TotResExp, the econometric model is specified by assuming that the vector of disturbances (ε_1, ε_2, ϵ_3, ϵ_4, ϵ_5) are have zero means and covariance with that is heteroskedastic with up to first order serial correlation.[6]

III. Model Estimates

Table 4 provides estimated coefficients, robust standard errors, z statistics, p values and 95 percent confidence interval estimates for the structural equations of the model.

Although Table 4 reports university- or research center-specific intercept estimates, these are not the focus of interest. Nonetheless, the correct interpretation is provided. For example, in the equation for disclosures of inventions to the TTO, the estimated constant, 10.765, is an estimate of the intercept for the group of universities that reported anonymously. The coefficient -9.415for LSU_AG (the LSU Agriculture Center) is an estimate of the difference between the intercept for the unknown group of universities (10.765) and the LSU Agriculture Center. Therefore the hypothesis being tested by the z statistic is whether there is a difference between the intercept of the labeled university and the intercept of the unknown group of universities and this estimated difference is not significant at the 0.05 level of significance (p value = 0.062). The point estimate of the intercept for the LSU Agricultural Center 1.35, found by adding the Intercept in the equation with the estimated difference for LSU_AG (i.e., 1.35=10.765-9.415). Estimates of the intercepts for other institutions and in other equations may be obtained similarly.

Table 4*Structural model estimates*

	Coefficient	HAC Std.Err.	z	P>|z|	95% LCL	95% UCL
InvDisRes						
Constant	10.765	4.325	2.490	0.013	2.287	19.242
LSU_AG	-9.415	5.037	-1.870	0.062	-19.287	0.456
LATECH	1.760	4.355	0.400	0.686	-6.776	10.297
TULANE	-13.927	4.577	-3.040	0.002	-22.898	-4.956
UNO	-8.153	4.614	-1.770	0.077	-17.197	0.891
LSU	-6.858	4.051	-1.690	0.090	-14.797	1.082

[6]In Stata, the estimator is implemented as a twostep GMM estimator via the gmm command with the option wmatrix(hacnwest 1).

TotResExp	0.054	0.031	1.740	0.081	-0.007	0.116
TotFTE	8.018	1.229	6.520	0.000	5.609	10.427
LicIss						
Constant	0.331	2.903	0.110	0.909	-5.359	6.020
LSU_AG	0.878	2.752	0.320	0.750	-4.516	6.272
LATECH	-0.519	2.551	-0.200	0.839	-5.519	4.480
TULANE	0.103	2.627	0.040	0.969	-5.045	5.251
UNO	-0.528	2.826	-0.190	0.852	-6.068	5.011
LSU	0.768	2.752	0.280	0.780	-4.626	6.161
LegFees	2.197	0.846	2.600	0.009	0.538	3.856
InvDisRec	0.113	0.021	5.450	0.000	0.072	0.154
StUpsFormed						
Constant	-0.100	1.992	-0.050	0.960	-4.005	3.805
LSU_AG	0.485	1.718	0.280	0.778	-2.882	3.852
LATECH	-0.396	4.151	-0.100	0.924	-8.531	7.739
TULANE	-0.538	1.667	-0.320	0.747	-3.806	2.729
UNO	0.763	2.013	0.380	0.705	-3.183	4.709
LSU	0.875	1.058	0.830	0.408	-1.200	2.950
InvDisRec	0.018	0.015	1.190	0.234	-0.012	0.048
LegFees	1.346	0.286	4.710	0.000	0.786	1.907
PatAppFld						
Constant	-3.872	6.616	-0.590	0.558	-16.840	9.095
LSU_AG	6.068	5.577	1.090	0.277	-4.862	16.999
LATECH	4.616	5.381	0.860	0.391	-5.931	15.163
TULANE	2.492	5.797	0.430	0.667	-8.871	13.854
UNO	4.227	6.405	0.660	0.509	-8.326	16.780
LSU	11.265	4.414	2.550	0.011	2.613	19.917
InvDisRec	0.500	0.071	6.990	0.000	0.360	0.640
LegFees	10.238	2.512	4.080	0.000	5.315	15.161

(continued)

	Coefficient	HAC Std.Err.	z	P>|z|	95% LCL	95% UCL
GrossLicInc						
Constant	3.492	0.794	4.400	0.000	1.937	5.048
LSU_AG	-3.436	0.786	-4.370	0.000	-4.977	-1.895
LATECH	-4.244	0.740	-5.730	0.000	-5.695	-2.793
TULANE	0.920	0.840	1.090	0.274	-0.728	2.567
UNO	-3.819	0.773	-4.940	0.000	-5.335	-2.303

LSU	-3.844	0.805	-4.770	0.000	-5.422	-2.266
LicGenInc	0.114	0.011	10.030	0.000	0.092	0.137

Turning to the structural equation estimates of parameters of interest in each equation, in the equation for *InvDisRec*, the average number of inventions disclosed by the TTO increases by 8.018for each additional FTE at the TTO, which is statistically significant at less than the 0.001 level of significance. For total research expenditures by the university, the point estimate in TotResExp suggests an additional 0.054 inventions for each additional million dollars of research expenditure, with the p value of 0.081implying weaker evidence that this coefficient is different than zero. The model's lack of detailed information of what departments spend research dollars for each university presumably explains the lack of precision of this estimate. Recalling that the standard deviation of research expenditures in the is 173.84 (Table 2), the point estimate 0.054 implies that a one standard deviation increase in research expenditures leads to approximately nine more inventions per year.

For the structural equation for licenses issued in the survey year, *LicIss*, each additional million dollars of legal fees is associated with an increase of 2.197licenses issued and each additional invention is associated with 0.113 additional licenses, with both of these estimates significantly different than zero at the 0.01 level of significance. Inverting 0.113 suggests that nearly 9 additional inventions are required to generate one additional license.

For the structural equation for the number of startups formed, *StUpsFormed*, each additional invention increases the average number of startups formed by an estimated 0.018, implying 55 new inventions are required for a new startup. However, the p value of the estimate, 0.184, suggests there is not strong evidence that the estimated coefficient for inventions is different than zero. Again, additional information on which departments within universities are inventing would probably improve precision here, since as discussed earlier new products differ in the ease with which a startup can produce and market them. Each additional million dollars in legal fees is associated with 1.346new startups, and the null hypothesis that the population parameter is zero can be rejected at less than the 0.001 level of significance.[7]

[7]A model with proportion of research expenditures funded by industry in this equation was also estimated but the p value on this variable was 0.92, so the variable was omitted from the reported model.

For the structural equation on total number of patent applications filed, the average number of patent applications filed increases by 0.500for each invention disclosed, which is significantly different than zero at less than the 0.001 level of significance and implies that roughly half of new inventions are patented. Each additional one million dollars in legal fees is associated with an average of 10.238new patents, which is significant at less than the 0.001 level of significance. Viewed alternatively as the cost of patenting and perhaps also subsequently defending patent rights the estimated coefficient on legal fees suggest a patent has approximately $98,000 in legal fees associated with it.[8]

For the structural equation for annual license income, *GrossLicInc*, the estimated coefficient on licenses that are generating incomes, *LicGenInc*, is 0.114, implying that each license that generates income adds $114,000 per year to gross license income, and the estimated coefficient is statistically significantly different than zero at less than the 0.001 level of significance.

One indicator of the goodness of fit of the model can be obtained by substituting sample values into the structural equations to obtain predictions and then investigating the sample correlations between the predicted values and the actual variables. The sample correlations between actual values of the endogenous variables and their predicted values from the structural equations are given in Table 5. The square of the sample correlation is R squared, which is a measure of how much variation in the endogenous variables is explained by the predicted values, and is also given in Table 5. Observe that all of the sample correlations are statistically significant at the 0.05 level of significance and the values of R square indicate quite good fits for each equation, ranging from 0.68 for licenses issued to 0.96 for inventions disclosed.

Table 5 *Correlations between predicted and actual values for endogenous variables*

[8]The data set also contains a variable "reimbursements of legal fees" which would substantially reduce the net legal fees to the university. Gross legal fees were used rather than legal fees net of reimbursements because reimbursements are speculative at the time a decision is made to spend.

Variables	Sample correlation coefficient	R squared
InvDisRec, predicted *InvDisRec*	0.98	0.96
LicIss, predicted *LicIss*	0.82	0.68
StUpsFormed, predicted *StUpsFormed*	0.86	0.74
TotPatAppFld, predicted *TotPatAppFld*	0.87	0.76
GrossLicInc, predicted *GrossLicInc*	0.91	0.82

One diagnostic test for the GMM system estimator is provided by Hansen's J test. Hansen's J test tests the null hypothesis that the instruments that were used (*LegFees*, *TotFTE*, *LicGenInc, TotResExp*) are orthogonal to the population disturbances in each equation in the structural model. The test statistic follows a chi square distribution with (l-k) degrees of freedom, where l is the number of moment restrictions and k is the number of parameters. The model above implies 50 moment restrictions and has 39 parameters, and the value of the J statistic is 15.47 with an associated p value of 0.1618. Therefore there is very weak evidence that our instruments are not orthogonal to the population structural disturbances. It is also possible that the evidence against the null hypothesis is due to serial correlation additional serial correlation unaccounted for by the HAC estimator.[9]

Conclusion

This research estimates a structural equation model that relates inputs to the technology transfer process, TTO staff levels, university research expenditures and legal fees and licenses that generate income (many from previous years) to outputs of the technology transfer process, current inventions, current license agreements, current startups,current patents and gross license revenues. Despite the data set's lack of identifying information for a large portion of the sample, sample correlations between predicted values and actual values of the endogenous variables range from 0.68 to 0.98 and indicate quite good fits.

The model can be used for several purposes because it provides fairly reliable estimates related to the economics of technology transfer. For example, our estimates imply that the average license which generates income generates $114,000 in revenue annually and that a patent filing costs roughly $98,000 in legal fees. They also provide some indication of the

[9]A discussion of the test is contained in Stata Corp (2011, p. 695)

productivity of TTO personnel. Previous research focused on efficiency indicates that TTO personnel do not enhance university efficiency in generating license revenues (Link and Siegel 2005). But the broader, system approach taken here clarifies that TTO personnel play a critical role upstream from the generation of licenses and license revenues in simple disclosure of inventions.

There is weak evidence that the orthogonality conditions required by the GMM estimator used do not hold in the population, or equivalently, that some of the variables that we have treated as exogenous are in fact endogenous. In practice, it is likely that legal expenditures and perhaps also TTO staffing levels are chosen by university administrators who have knowledge of their institution, such the extent to which the cultureand financial incentives support collaboration with private industry and the presence of "star" researchers or unique centers of excellence that these choices are conditioned on. A second possible explanation for the evidence that the orthogonality conditions do not hold is serial correlation in the endogenous variables which was only imperfectly modeled here with dummy variables and a robust covariance estimator. However, these shortcomings provide guidance for better models that incorporate more data.

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