Behind the Curtain: An Analysis of Internal TTO Programs

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ABSTRACT

Using the AUTM Statistics Access for Technology Transfer database and a personal survey of 86 universities, I examine the effects of a variety of internal technology transfer office programs on technology transfer performance. The main findings are that equity-intensive investment policies are shown to have a positive impact on university startup formation and mentoring programs increase the number of licensing agreements a university executes by 20 to 22 percent. Innovation award programs, iBridge network membership, and express licenses have no significant effect on the number of licensing agreements a TTO generates. To the best of my knowledge, no previous studies have examined the effects of multiple internal TTO programs on technology transfer performance.
1. INTRODUCTION

Universities play a critical role in spurring technological progress within the United States. In 2004, the University Technology Transfer industry reported over $1 billion in licensing income, and provided firms with $20 to $50 billion worth of inventions (Cardozo et al. 2011). University technology transfer is the process by which advances in basic research conducted at universities are translated into marketable products. Technology transfer provides firms with superior products, processes, services, and lower costs of research. Academic institutions also benefit from technology transfer, as successfully commercialized inventions boost the reputation of the academic institution, provide the opportunity for faculty to be financially compensated through royalties, and offer the potential for stronger university-firm partnerships in the future. Technology transfer benefits society as a whole through incentivizing universities to focus their research on ideas that will have tangible benefits for consumers. A wide-variety of groundbreaking products have been created at universities, including Google, fluoride toothpaste, the polio vaccine, the pacemaker, rocket fuel, vitamin D, seat belts, and MRI technology.

Universities conduct 60 percent of basic research activities in the US (Grueber & Studt 2013). Basic research forms the foundation for innovation, as it is characterized by attempts to gain greater understanding of particular phenomena with no commercial application of the findings in mind. Publishing this basic research, however, does not ensure that relevant firms and institutions will take advantage of this research, and continue to develop the results. The “risk of a vast amount of research results with a high commercial potential remaining in laboratory shelves is a major concern of policy
makers” (Sampat 2006), and legislation that reflects this exact concern includes the Stevenson-Wydler Technology Innovation Act of 1980, Bayh-Dole Act, National Competitiveness Technology Transfer Act of 1989, and the National Technology Transfer and Advancement Act of 1996, among others. These laws are aligned with federal efforts to incentivize universities to become more active participants in the technology transfer process. The Stevenson-Wydler Act, for example, forces universities and federal laboratories to dedicate a proportion of their budgets for the sole purpose of technology transfer activities.

The increasing prevalence of university technology transfer offices, also known as TTOs, suggests that academic institutions are exerting greater efforts to translate research results into marketable products. In 1991, only 56 Technology Transfer Offices were listed under the Association of University Technology Managers database, but by 2012, this number had increased to 155. Despite the increased desire of academic institutions to commercialize inventions and the passage of multiple bills designed to ease university-industry technology transfer, numerous studies indicate that universities remain inefficient distributors of the inventions they create. A survey by Thursby & Thursby (2000) found considerable evidence of poor university-industry relations; 66 percent of firms surveyed had never licensed a university invention. Lerner (2002) finds that there is a scarcity of academic patents in the financial services industry, and Siegel et al. (2003) find that incentives for faculty innovation and commercialization are not aligned. In addition, AUTM data reveals that universities generate low returns on research investments, with average licensing income constituting only 3.1 percent of total research expenditures in 2012. Moreover, academic institutions only spend 0.6 percent of their
research budgets on technology transfer, and only 16 percent of technology transfer offices generate more revenue than their total operating and research costs (Abrams et al. 2009). The majority of university licensing revenue is generated by only a handful of universities from breakthrough inventions; Northwestern and New York University have earned 1.48 and $1.88 billion from 2002 to 2011 largely due to the royalties generated by the prescription drugs Remicade and Lyrica.

Policy makers have attempted to improve university technology transfer, but there are also steps universities can take to more efficiently allocate academic inventions towards industrial applications. The wide variance of university licensing incomes suggests that many universities would benefit greatly from adapting the best practices of the most effective technology transfer programs. Siegel et al. (2003) attempt and fail to explain the differences in technology transfer performance solely through structural and environmental characteristics using stochastic frontier estimation, a method of determining the optimal balance of inputs to maximize output. The authors suggest that organizational and internal policies, which were not included in their SFE analysis, may play a large role in TTO success. In this study I ask the question, “Which internal technology transfer office policies and programs lead to successful commercialization of more inventions?” The majority of previous papers related to this question have focused on inherent characteristics of universities, such as age, size, the presence of a medical school, and geographic location. In terms of aiding TTO directors in determining how to improve performance, previous analysis of structural university characteristics lack practicality because most variables cannot easily be changed. TTOs do not have the power to change school size or faculty quality to meet technology transfer objectives.
This paper focuses on the impact of certain TTO programs and policies on technology transfer performance. This research is more likely to provide feasible suggestions for optimizing TTO performance since the policies analyzed in this thesis are flexible and not costly to implement. Most of the following TTO programs have received little attention in previous literature, largely due to the confidential nature of TTO operations and a lack of data pertaining to this topic. Using the AUTM Statistics Access for Tech Transfer database, and a survey to which 86 universities responded, I measure the impact of equity policies, express licensing programs, mentoring programs, innovation award programs, and iBridge membership on TTO performance. The main findings are that equity-intensive investment policies are shown to have a positive impact on university startup formation, and mentoring programs increase the number of licensing agreements a university executes by 20 to 22%. Innovation awards, iBridge network membership, and express licensing programs have no significant effect on the number of licensing agreements and invention disclosures a TTO generates.

2. LITERATURE REVIEW

2.1 Licensing Process

Before evaluating the efficiency of previous university licensing operations, it is important to outline the basic commercialization process. First, faculty disclose their inventions to the TTO. Invention disclosures are the main inputs that the TTO works with to create licensing agreements. The more invention disclosures a TTO receives, the greater is the potential for developing new commercial products. The university then values the innovation, and determines whether or not it is appropriate to patent. After the university has filed for a patent, the invention is marketed to firms and entrepreneurs who
have interest in adapting this new technology. The invention is transferred to an existing or new firm via a licensing agreement.

Licensing agreements specify the timing and magnitude of royalty and licensing fees that the firm pays in exchange for university technology. Licenses also specify procedures to undertake in the event of legal disputes and how long the technology can be used for. Licensing fees are the most common way for universities to extract revenue. Djokovic and Souitaris (2008) define a university startup as, “a new company founded to exploit a piece of intellectual property within an academic institution.” Startup formation is important to analyze, as it is becoming an increasing prevalent mechanism of technology transfer, and possesses unique advantages from traditional licensing processes.

Licensing agreements with both existing firms and startup companies generate licensing income, although universities capture a higher proportion of the returns on startup companies (Valvidia 2013). Markman et al. (2005) found that about three quarters of university inventions are transferred to existing firms, and the other quarter are commercialized through startup companies. In this thesis, I include the number of invention disclosures received, licenses executed, and startups created per university per year as dependent variables.

2.2 Determinants of TTO Performance

The majority of academic papers investigating the determinants of technology transfer performance have examined structural characteristics of technology transfer offices. Previously measured university traits include TTO age, the presence of a
medical school, number of licensing staff, number of personal contacts between firm and industry, university size, and faculty quality.

Research has proven TTO experience to be a strong determinant of commercialization performance. Multiple papers have found the age coefficient to be positive and significant in regressions on university licensing revenue and licensing agreements executed (Cardozo & Strauss 2010; Carlsson & Fridh 2002; Feldman et al. 2002). In addition to age, size has also been proven to be a strong predictor of TTO success. Both Siegel et al. (2003) and Carlsson & Fridh (2002) find invention disclosures (a proxy for TTO size) to be positively correlated with commercial output and licensing revenue. Cardozo & Strauss (2010) employ research funding, another proxy for TTO size, in addition to invention disclosures and find similar results. Macho-Stadler et al. (2007) find a non-linear relationship between licensing revenue and TTO size: once the TTO expands past a critical volume of invention disclosures, the university experiences increasing returns to scale of licensing income.

Research of the effects of TTO staff and medical schools on technology transfer performance has produced mixed results. Siegel et al. (2003) use a stochastic frontier estimation to quantitatively measure TTO productivity, and find that hiring more TTO staff has no effect on licensing revenue. Thursby & Kemp (2002) and Rogers (2000) find increasing university staff improves licensing output. Di Gregorio & Shane (2003) find faculty quality is positively correlated with startup formation activity. Thursby & Kemp (2002) use a logit regression to find that universities with medical schools are less efficient at technology transfer. In an OLS regression on licensing output (the number of licensing agreements generated per university per year), Thursby et al. (2001) find that
holding all other explanatory variables constant, the coefficient on medical schools is positive and significant.

The main internal TTO policy that previous literature has focused on is inventor royalty compensation programs. Survey evidence from Thursby & Thursby (2001) indicates that university faculty highly value the proportion of royalties they receive in the event their invention becomes a successfully commercialized product. This leads the authors to conclude that greater financial compensation may yield greater inventive output. Siegel et al. (2003) support this finding, as analysis of their qualitative survey suggests that faculty rewards systems, and methods of facilitating university-industry relations are most important for increasing licensing output. Lach & Schankerman (2003) find that increasing royalty share by 10 percent increases revenue by 14 percent, holding all other explanatory variables constant. Friedman & Silberman (2003) also find strong evidence for a positive relationship between royalty shares and licensing incomes.

2.3 Variables of Interest

This paper aims to offer unique insight into university technology transfer best practices through analysis of the effect of certain internal TTO policies and programs on technology transfer performance. Specifically, I measure the effectiveness of equity policies, express licenses, mentoring programs, innovation awards, and iBridge network membership on license agreement and startup formation. A summary of my five hypotheses and predicted coefficient signs can be found in Table 1. Currently, almost no empirical analyses that measure the effectiveness of these programs exist, despite the fact that uptake rates of these programs ranged from 17 to 53 percent of universities sampled.
in my survey. Below I describe the related literature and hypotheses regarding each of
my five variables of interests.

2.31 Equity Policies

Hypothesis: *Universities that are more willing to hold equity positions in startup
companies will create more new firms via technology transfer.*

Equity policies represent a university’s willingness to invest stock in the startups
it helps to create. Evidence from Hsu & Bernstein (1997) suggests that financing
structure is a major determinant of whether or not a new firm decides to license a
university invention. The majority of startup directors sampled in their case studies
stated that they “would not have considered a startup without the ability to offer equity in
lieu of upfront fees” (Hsu & Bernstein, 1997, p. 13). My equity policy analysis builds on
the work of DiGregorio & Shane (2003), who employ a negative binomial model to find
that universities with equity intensive policies are 1.68 times more likely to generate
startups than universities with non-intensive equity policies.

Startups may prefer equity payments to universities in place of licensing fees for a
number of reasons. Startups lack sources of revenue in early stages of development, and
large, upfront licensing fees in lieu of stock payments further drain startups of much
needed liquidity. Equity compensation schemes allow new firms to allocate scarce funds
toward further product development. Licensing fees typically range from $10,000 to
$50,000, but have been known to reach sums as high as $250,000 (Bray & Lee 2000).

Equity deals are also easier to negotiate. Traditional methods of generating
startups without equity often include complicated systems of upfront fees and milestone
payments. In order to determine the magnitude of these payments, universities and
entrepreneurs must estimate the future market value of the negotiated invention, an especially difficult task considering many university innovations are often in very early “proof of concept” stages when they are sold to firms. Negotiations between the university and new firm may fail due to highly different valuations of the university innovation. With equity deals, speculation on the future value of the invention is not necessary, as financial compensation for the university is dependent on the success of the corresponding startup. Feldman, Feller, Bercovitz, & Burton (2002) mention the first equity deal Johns Hopkins University engaged in occurred largely because the high appreciation faculty had for the new invention was not shared by industry experts. Equity financing provided the best method of creating a licensing agreement that satisfies both university staff and the negotiating party.

The linkage of university revenue to the stock price of a startup also aligns university and startup incentives. Startup entrepreneurs possess great interest in aligning university incentives with the new firm, as further development of the invention may require substantial involvement of the inventors within the university faculty (Powers & McDougall 2005).

According to Bradley et al. (2013), “The ongoing involvement of the university scientist is especially crucial. Without input and contribution from the scientist, adaptation and use of transferred technology is unlikely to occur. The scientist has the greatest understanding of the invention and potential and can be indispensable in directing development and choosing the most capable firm” (p. 30).
The alignment of university and startup incentives through equity stakes may reduce the potential for legal conflicts for the startup, which often occur in technology transfer. Legal disputes can be quite costly for TTOs. According to Johns Hopkins 2012 Annual Technology Transfer report, legal expenses were $6.5 million, over half of their revenue of $12.2 million (FY 2012 Annual Report: Windows of Innovation, 2012). Increasing recognition of the benefits of equity financing help to explain its increased prevalence in recent years. In the AUTM database, the total number of startups with university equity stakes generated per year has increased from 198 to 313 from 2000 to 2012 (Figure 1).

This thesis is similar to DiGregorio and Shane (2003) in that both analyses use the AUTM database and examine the relationship between startup formation and willingness of a university to invest equity during negotiations between the TTO and new firm. This thesis attempts to improve the work of DiGregorio & Shane (2003) by using a larger dataset, utilizing a more accurate measure of university willingness to invest equity, and employing more models to ensure more robust results.

To measure the willingness of a university to invest equity in a startup, DiGregorio and Shane (2003) use a dummy variable that records a university as “equity intensive” if it engaged in at least one licensing agreement with equity during the previous year. One shortcoming of this proxy is that it creates a bias towards larger universities. A university that generates 100 licenses is more likely to take an equity stake in at least one of them than a university that only generates 10 licenses, even if in reality both universities share an equal willingness to invest stock in new firms. I aim to improve this issue with the proxy for equity intensity by measuring the proportion, rather
than total number, of startups that receive equity investments (number of startups generated that receive equity per university per year/ total number of startups generated per university per year). I refer to this variable as eqint. The value of this variable ranges from 0, no equity investments in university startups, to 1, equity stakes in all university startups. To avoid restricting the sample size to universities that have generated at least one startup, I specify for all universities that generate zero startups in a given year to have an eqint value of zero as opposed to being undefined. Similar to DiGregorio & Shane (2003), I lag the variable by one year to avoid the correlation between startup formation and eqint that will occur if both values are calculated in the same year. A correlation between eqint and startup activity in the same year occurs because a university that generates zero startups will have an equity intensity of zero as well for that particular year.

The second issue with the proxy for equity intensity in DiGregorio & Shane (2003) is that it measures licensing agreements that include equity. A licensing agreement can involve not only contracts with startups, but existing firms as well. It is therefore possible that a university listed as having an “equity intensive” startup policy in DiGregorio & Shane (2003) may have never actually taken an equity stake in a startup. I correct this problem by exclusively measuring startup contracts that involve equity payments. I am able to use this measure by importing a variable, stupeq, to my dataset that was added to the AUTM database in 2000. This variable, stupeq, specifically measures the number of startups that a university invests equity in for a given year.

My analysis of equity policies on startup formation is also superior in the sense that my dataset is larger. DiGregorio & Shane (2003) use 5 years of panel data for 101
universities whereas for this thesis, I use twelve years of panel data for 189 universities. Finally, my analysis employs a wider array of econometric models to ensure more robust results. This thesis utilizes Tobit, negative binomial, and zero-inflated negative binomial regressions to analyze the effect of equity policies on startup activity. DiGregorio and Shane (2003) only use a standard negative binomial model.

2.32 Mentoring Programs

_Hypothesis 2: Universities that have implemented formal technology transfer mentoring programs will receive a greater quantity of invention disclosures and execute more licensing agreements_

University faculty have the expertise to produce valuable inventions, but often lack the entrepreneurial skills and business savvy to take these products to the market. Mentoring programs help to bridge the gap between academia and industry through educating faculty about technology transfer and aiding them throughout the commercialization process. Mentorship programs pair entrepreneurs, TTO faculty, business school staff, and other entrepreneurial experts with university professors to help them evaluate the market potential of research results, raise capital, and refer faculty to business contacts. Business contacts may include potential investors, legal experts, industry experts, and other experienced entrepreneurs.

Survey results from Thursby et al. (2001) indicate that eliciting invention disclosures from faculty is a major issue for many TTOs, and mentoring programs are intended to increase the quantity of invention disclosures a technology transfer office receives. Frequent interaction with the technology transfer office, faculty knowledge of how technology transfer works, and the convenience of the invention disclosure process
are key determinants of how many invention disclosures a university receives (Owen-Smith & Powell 2001); mentoring programs help to improve each one of the above inputs of the invention disclosure function.

Mentoring programs may also help to increase the proportion of invention disclosures a TTO translates into licensing agreements. Generally, only about 1/12 of university invention disclosures are licensed (Carlsson & Fridh 2002). The expertise of a quality mentor, along with the increased access to capital, investors, potential licensors, and industry professionals that he or she can provide, should help the TTO translate more invention disclosures into marketable products.

2.33 Innovation Award

_Hypothesis 3: Universities that recognize faculty for outstanding efforts in technology transfer with an innovation award will receive a greater number of invention disclosures and execute more licensing agreements._

An innovation award is an annual or semi-annual award that recognizes professors for their outstanding efforts in the development or commercialization of an invention. Many studies within the field of technology transfer have examined how incentives can affect the quantity and quality of inventive output a university employee produces. Royalty share, the percentage of revenue the inventor will be allocated in the event that his/her invention is commercialized, has been found to have a large effect on the effort put forth by the professor in the innovation process (Friedman & Silberman 2003; Lach & Schankerman 2003).

Recognition is an incentive that has largely been ignored in university technology transfer literature despite that fact that research in other fields indicates public recognition
mildly increases employee effort. In an experimental study, Bradler et al. (2013) found that public recognition of the top three performers on a 2-hour data entry task improved subsequent performance of the entire group of workers by 7.2 percent. University faculty may seek to improve their chances of achieving tenure through improving their academic visibility. The technology licensing process offers a unique channel for professors to improve prominence and reputation within the university (Baycan & Stough 2012). In addition to the monetary compensation sometimes associated with an academic award, university professors will be incentivized to commercialize innovations discovered within their field to the best of their ability, as successful commercialization will lead to improved chances of receiving tenure. Lockett & Wright (2005) provide empirical evidence for this theory by using a survey to find that recognition within the university and scientific community is the largest incentive for university professors. My hypothesis is that innovation awards recognizing faculty for outstanding accomplishments in the field of technology transfer will increase effort from university professors in producing and disclosing inventions. Innovation awards may also improve the quality of the invention disclosures, thus aiding the TTO in executing more licensing agreements.

2.34 Express Licenses

Hypothesis 4: Universities that have an express licensing option for firms will execute more technology transfer contracts.

Express licenses are standardized contracts used to facilitate the university technology transfer process. Most universities produce a diverse array of inventions, and consequently, most technology transfer agreements vary significantly in terms of deal
structure. Express licenses significantly reduce the length of the negotiation process through providing a uniform technology transfer contract option that can be signed with minimal negotiation. Traditionally, licensing agreements are created through a lengthy process in which TTO faculty and the firm interested in the innovation work together to create a contract that can be agreed upon by both parties. This process consists of multiple rounds of negotiation, with many complex deal structures being discussed. Frequent disagreements over the valuation of the invention, payment structure, or how the invention is defined all serve to slow down this negotiation process. With traditional licenses, the TTO must also conduct due diligence prior to engaging in negotiations with the firm, which involves heavy research of the university innovation from a commercial and legal standpoint. Express licenses significantly reduce the time it takes for an interested party to license an invention, as the TTO need not conduct any due diligence and interested parties are presented with an immediate set of licensing terms. Multiple rounds of negotiation are not needed. Generally, the terms of a licensing agreement are favorable towards the licensing party, as the goal of express licensing programs is to maximize university technology transfer, not revenue.

Swamidass & Vulasa (2008) find evidence that many TTOs are understaffed, and will often sacrifice time dedicated to marketing activities to ensure more technical duties are completed. Express licenses significantly lower the cost of creating and negotiating a licensing agreement, which should allow employees to allot more time towards marketing and other activities necessary for the successful commercialization of a university invention. DeSimone & Mitchell (2010) further suggest that express licenses may also prevent the implementation of “counterproductive startup arrangements involving
university licenses” that prioritize immediate financial compensation of the university over the growth and development of the new university spin-off.

Allowing persons interested in licensing a university invention to select a “default” licensing contract option may also appeal to a more diverse array of potential entrepreneurs. Firms less knowledgeable about the licensing process may prefer to select an option that has been chosen by experienced university faculty, whereas more sophisticated entrepreneurs may turn down the express licensing contract and choose to engage in more complex negotiations. Thaler & Sunstein (2008) apply similar logic for recommending the implementation of a simple, default option for company 401(k) plans “to fit the needs of participants who have various levels of interest and sophistication (p. 130).”

First adopted by the University of North Carolina, express licenses are becoming an increasingly popular practice among universities, and are attracting growing public debate as well. The Association of American Universities does not recommend the usage of uniform licensing agreements, referring to express licenses as “insufficient ‘cookie-cutter’ solutions.” The AAU further recommends for TTOs to “analyze each licensing opportunity individually in a manner that reflects the business needs and values of their institution (Association of American Universities, 2007, p. 1).”

2.35 iBridge Network

_Hypothesis 5: Universities that are members of the iBridge Network will complete more technology transfer agreements._

The iBridge Network is an online resource where venture capitalists and firms can learn about university innovations and express interest in the inventions they want to
license. Universities and research centers post descriptions of marketable innovations on the website, along with potential terms of agreement in order to license the technology. Venture capitalists and other seekers of innovative output can search the website based on field of research and product application. Founded in 2005 by The Kauffman Foundation, the iBridge Network currently lists over 22,000 inventions from 169 universities and research foundations.

Technology transfer offices have a duty to establish networks of potential invention licensors (Mitchell 1991) and the iBridge network helps the university to accomplish this goal. Through increasing the exposure and visibility of university inventions, the iBridge Network is intended to improve the quantity of inventions a university commercializes. Online methods are among the least preferred procedures for marketing university inventions according to a survey by Thursby, Thursby, & Jensen (2003), yet the website may still be a valuable channel for the matching of university inventions with potential entrepreneurs.

3. METHODOLOGY

3.1 Data

I merge three datasets in my analysis. The AUTM Statistics Access for Tech Transfer database constitutes the majority of the dataset, and is the source from which I derive all of my dependent variables. Started in 1991, AUTM STATT is a widely cited source of information that uses an annual survey to obtain information about university technology transfer performance in the US. I drop all universities from the AUTM dataset that do not have at least two years worth of observations. In order to control for differences in school size, yearly, school-specific enrollment information from the
National Center for Education Statistics database was also merged to the master dataset. I use this dataset to measure the relationship between $eqint$ and startup formation.

The modified AUTM dataset is then merged with results from a survey I collected in February 2014 to examine the relationship between technology transfer performance and four distinct TTO programs: express licenses, innovation awards, mentoring programs, and iBridge network membership. The survey was designed to be quick and simple to complete. Participants had to respond to two questions for four different TTO policies: express licensing programs, mentoring programs, award programs, and iBridge membership. A copy of my February 2014 survey can be found in the Supplements folder under the filename ReingruberSurvey.pdf. The questions were:

1. Does your technology use this particular policy/program?
2. If so, in which year was this policy or program implemented?

The majority of non-responses from universities were due to confidentiality issues or new employees not being aware of TTO practices that may have been implemented in the past before they were hired. By 2012, 31 out of 86 universities were iBridge members, 15 out of 86 universities implemented an express licensing program, 35 out of 84 universities had an innovation award program, and 45 out of 85 universities installed a formal mentoring program.

### 3.2 Explanatory Variables

Summary statistics for all dependent and independent variables employed in this thesis are listed in Table 2. The explanatory variables used in this thesis are TTO age ($age$), enrollment ($enrollment$), federal research funding ($ln\_fedexp$), industrial research funding ($ln\_indexp$), the number of licensing staff ($ln\_licfte$), and the number of invention
disclosures the TTO receives, lagged by four years \((ln\_lagdisc)\). I also include state \((i\_state)\), university \((i\_id)\), and year \((i\_year)\) dummy variables to employ state, time, and university fixed effects. Federal and industrial research funding represent major inputs of the university technology development process; in the primary dataset, the mean value of annual funding provided to a given university was $190 million in federal expenditures, and $20 million in industrial expenditures. Invention disclosures are known as the “raw material” of TTOs (Friedman & Silberman 2003). They are confidential forms written by faculty that ask the TTO to evaluate whether some product of their research should receive patent protection. About a quarter of invention disclosures eventually become patented (Carlsson & Fridh 2002). The number of invention disclosures received per year is lagged by four years to represent the average amount of time it takes for an invention disclosure to reach a licensing or startup agreement (Markman et al. 2005).

TTO age serves as a useful proxy for licensing experience. The number of TTO full-time employees, \(ln\_tofte\), and undergraduate and graduate students, \(enrollment\), control for the size of the TTO and the university. The distributions of invention disclosures received, number of licensing staff, federal research funding, and industrial research funding are all positively skewed. To make the observations follow a more normal distribution, I transform the variables by taking the natural log of one plus the given variable.

### 3.3 Explained Variables

The dependent variables I analyze are startup formation \((strtup)\), licenses executed \((ln\_lexec)\), and invention disclosures received \((ln\_invdis)\). I take the natural log of licenses and invention disclosures, but not of \(strtup\) due to differences in the methodology I use between the three variables.
The measurement of TTO output has long been a source of debate within the field of technology transfer, and successful commercialization efforts have been evaluated through a wide array of dimensions. Licenses, patents, invention disclosures, startups, federal and industrial research funding, licensing income, licenses that generate over $1 million in royalties, and licensing yields (licensing income/ research funding) are all measures of TTO output that have been used to evaluate TTO performance in the past.

Thursby et al. (2001) conduct a survey of 62 universities asking TTO managers and faculty to rank the importance of technology transfer outputs. Responses varied widely between universities, but revenue maximization was found to be the most important objective. Increasing the number of licenses executed was the second most popular objective. A more recent paper by Abrams et al. (2009) finds different results in a survey of 130 colleges, where faculty service and the “translation of research results” represented the most popular technology transfer goals, receiving 39.2 percent and 34.6 percent votes for highest TTO priority. Revenue maximization was ranked as a top priority for only 11.5 percent of the universities. This thesis uses the second most popular measure of output (translation of research results) from Abrams et al. (2009) to measure TTO performance, as their survey is a more current reflection of TTO objectives, and is more aligned with the fundamental purpose of technology transfer: to move university inventions out of the lab towards industrial applications. Furthermore, measurement of the relationship between TTO characteristics and revenue maximization poses many challenges, as newly licenses inventions tend to not generate returns to the universities through royalties until about 3 to 7 years later (Friedman & Silberman 2003).

3.4 Primary Analysis: Effects of Equity Policies on University Startup Formation
For the primary analysis, investigating the effects of equity-friendly TTO policies on startup formation, the dependent variable, \textit{startup}, has many unique properties. It consists of positive integers with relatively few unique values: 80.2 percent of universities per year generate four or fewer startups and 29.4 percent of universities do not create any start-ups at all in a given year (Figure 2). The \textit{startup} variable is also overdispersed; the variance of startup formation is five times higher than the mean. Overdispersion distorts measurement of standard errors and goodness of fit for tests for standard ordinary least squares regressions. The chi-squared likelihood ratio test indicates that the data is overdispersed at the 1 percent significance level. Finally, the dependent variable does not follow a normal distribution, as demonstrated by the histogram in Figure 3, where the \textit{startup} observations are clearly skewed towards zero.

Unlike for other dependent variables employed, such as \textit{ln\_lceexec} or \textit{ln\_invdis}, I am unable to transform the observations of \textit{startup} into a more normal distribution through taking the natural log. I generate a new variable called \textit{ln\_startup}, which is equal to the natural log of 1 + \textit{startup}, yet the distribution of the observations remains excessively skewed, as demonstrated in the histogram \textit{ln\_startup} in Figure 4.

I employ Tobit and negative binomial models in the primary analysis. The decision to use these two models stems from the fact that the dependent variable, \textit{startup}, has relatively few values, is overdispersed, and highly skewed towards zero.

After running an OLS regression on \textit{startup}, the White Test indicated that the dataset is heteroskedastic (Figure 5). White’s test rejected the null hypothesis of homoskedacity at the 1 percent significance level. I use robust standard errors to control for the observed heteroskedasticity. Figure 6, a scatter plot of the residuals against their
lagged values, shows little evidence of autocorrelation, as there appears to be no discernable linear relationship between the plotted values.

The first regression used is the Tobit model. To account for the clustering that occurs at zero (29.4% of universities in a given year do not generate a startup), the Tobit model is truncated at zero. The Tobit model is as follows:

\[
\text{str}tup_i^* = \beta_1 \text{invdisclag} + \beta_2 \text{ln_fedexp} + \beta_3 \text{ln_indexp} + \beta_4 \text{ln_totfte} \\
+ \beta_5 \text{enrollment} + \beta_6 \text{age} + \beta_7 \text{medschool} + \beta_8 \text{eqint} + \beta_9 \text{i.year} \\
+ \beta_{10} \text{i.state}
\]

\[
\text{str}tup_i = \text{str}tup_i^* \text{ if } \text{str}tup_i^* > 0 \\
\text{str}tup_i = 0 \text{ if } \text{str}tup_i^* \leq 0
\]

In a truncated Tobit model, the values of the explanatory variables are known only when the dependent variable is greater than zero. The Tobit model employs a latent variable \(y_i^*\) that is equal to \(y_i\) when \(y_i^*\) is greater than zero. The use of a latent variable in the Tobit model allows for \(\text{str}tup\) to have observations of zero, but also be continuously distributed over positive values.

The final two models in the primary analysis are negative binomial and zero-inflated negative binomial (ZINB) models. The negative binomial model is a variant of the Poisson model. The Poisson model assumes equidispersion, where the variance and the mean of the dependent variable are equal to one another. In practice, such an assumption often is not valid, and the negative binomial model employs a parameter, \(\alpha\), that controls for dependent variables that have larger variances than the mean. The negative binomial model assumes the following frequency function based on a Poisson-
Gamma distribution of the dependent variable.

\[ \Pr(Y = y | \mu, \alpha) = \frac{\Gamma(\alpha^{-1} + y) \cdot \left( \frac{\alpha^{-1}}{\alpha^{-1} + \mu} \right)^{\alpha^{-1}} \cdot \left( \frac{\mu}{\alpha^{-1} + \mu} \right)^y}{\Gamma(\alpha^{-1}) \cdot \Gamma(y + 1)} \]

The overdispersion parameter, \( \alpha \), is constant and typically ranges from .1 to 4. In my analysis, the dispersion parameter is .14. If it were zero, the model would be assuming a Poisson distribution. The variable \( \mu \) is represented by the equation:

\[ \mu = e^x \]

The zero-inflated variant of the negative binomial (ZINB) model is typically used for count data with an excessive number of observations recorded as zero. The zero-inflated model runs two separate regressions; one to predict whether or not the university will create a startup and the other to predict the number of startups generated given the fact that the university will create at least one startup. The zero-inflated negative binomial model in my analysis predicts whether or not a university will generate a startup based on university size, TTO size, TTO experience, and industry funding.

More important than analysis of the results of the ZINB regression is ensuring that the model is a good fit. I compare the ability of the ZINB to predict observations compared to more traditional models of count data analysis: Poisson and standard negative binomial regressions. The Poisson goodness of fit test indicates that the standard negative binomial model is a better fit than a Poisson regression at the 1 percent significance level. The fact that the variance of the dependent variable is overdispersed also supports this claim. I then use the Vuong Test (Vuong 1989) to verify that the ZINB model is a better measure of fit than the standard negative binomial. The Vuong test rejects the null hypothesis that the standard negative binomial model is a better fit at the
99 percent confidence level. Finally, in Figure 7, I graph the difference between observed and predicted values for the ZINB, standard negative binomial, and the poison regression models using the countfit Stata command (Long & Freese 2006). The graph indicates that the ZINB model has the lowest difference between observed and predicted values at nearly every count value, particularly zero and one. The maximum and mean residual values are also lower for the ZINB than the standard negative binomial or Poisson model. Results of the Vuong Test and the countfit command suggest DiGregorio & Shane (2003) may have benefited from including a ZINB regression in their analysis. They only use a standard negative binomial regression when examining the relationship between startup formation and equity policies despite the strong possibility that the ZINB model may have been a better fit given their dataset.

3.5 Secondary Analysis: Effects of internal TTO Policies on Invention Disclosures Received and Licenses Executed

The secondary analysis is where data from the survey collected in February 2014 is included in the regressions. The sample size of all regressions decreases significantly in the secondary analysis since only 86 of the universities in the AUTM database responded to the survey. I refrain from using count data models (negative binomial and ZINB regressions) in the secondary analysis due to major differences in the dependent variables I analyze (ln_lceexec and ln_invdis). One key difference is that unlike startup, I can sufficiently correct for the skewness of the two dependent variables I use in analysis of the survey data through taking the natural log of both lceexec and invdis. After this transformation, the dependent variables follow a more normal distribution appropriate for fulfilling Gauss-Markov assumptions (Figures 8 & 9). The dependent variables in the
secondary analysis also have many more unique integer values than the *startup* variable.

Values for licensing agreements range 0 to 313, with a median value of 39. The range for invention disclosures is 0 to 1,638, with a median value of 105.

Initial OLS regressions on *ln_invdis* and *ln_lcexec* violate two Gauss-Markov assumptions. The White Test indicates both regressions violate the null hypothesis of homoskedacity at the 1 percent significance level (Figures 10 & 11). The Durbin-Watson tests used for both regressions generate values of .63 and .90, both of which indicate positive autocorrelation at the 1 percent significance level. I correct for the heteroskedacity in the regression analysis through using robust standard errors. First order serial correlation is controlled for through the use of Prais-Winsten model.

The Prais-Winsten estimation (Prais & Winsten 1954) is a variation of the Cochrane-Orcutt model (Cochrane & Orcutt 1949) that allows for the inclusion of the first observation. The Prais-Winsten model controls for first order serial correlation. First order serial correlation implies that for

\[ Y_t = ax_t + bz_t + c + u_t \]

the error term is a function of the previous error term and white noise.

\[ u_t = \rho u_{t-1} + e_t \]

Serial correlation distorts the value of the standard errors and error variance of OLS regressions; however, serial correlation can be corrected for if the value of \( \rho \) is known. The Prais-Winsten regression predicts the value of the \( \rho \) through running the original OLS regression to find the value of the residual, \( u_t \). This residual value is then regressed on the residual value lagged one year before; \( u_t \) is regressed on \( u_{t-1} \) for \( t=1, 2, \) etc. The regression of the residuals on their lagged values generates a predicted value for \( \rho \), which
is then incorporated in the original OLS regression. The Prais-Winsten regression is an iterative process, computing a new set of residuals with a new value of \( \rho \) until \( \rho \) experiences little change from iteration to iteration.

The two general Prais-Wisten models I run are

\[
\ln_{\text{exec}} = \alpha \sqrt{1-\rho^2} + \left( \sqrt{1-\rho^2} \ a g e \right) \beta_1 + \left( \sqrt{1-\rho^2} \ m e d s c h o o l \right) \beta_2 \\
+ \left( \sqrt{1-\rho^2} \ l n _ { i n d e x p } \right) \beta_3 + \sqrt{1-\rho^2} \ l n _ { f e d e x p } \beta_4 \\
+ \sqrt{1-\rho^2} \ l n _ { t o t f t e } \beta_5 + \left( \sqrt{1-\rho^2} \ l n _ { i n v d i s c l a g } \right) \beta_6 \\
+ \left( \sqrt{1-\rho^2} \ e n r o l l m e n t \right) \beta_7 + \left( \sqrt{1-\rho^2} \ e l y e a r d u m m y \right) \beta_8 \\
+ \left( \sqrt{1-\rho^2} \ i b y e a r d u m m y \right) \beta_9 + \left( \sqrt{1-\rho^2} \ a y e a r d u m m y \right) \beta_{10} \\
+ \left( \sqrt{1-\rho^2} \ m y e a r d u m m y \right) \beta_{11} + \sqrt{1-\rho^2} \epsilon_1
\]

\[
\ln_{\text{invidis}} = \alpha \sqrt{1-\rho^2} + \left( \sqrt{1-\rho^2} \ a g e \right) \beta_1 + \left( \sqrt{1-\rho^2} \ m e d s c h o o l \right) \beta_2 \\
+ \left( \sqrt{1-\rho^2} \ l n _ { i n d e x p } \right) \beta_3 + \left( \sqrt{1-\rho^2} \ l n _ { f e d e x p } \right) \beta_4 \\
+ \left( \sqrt{1-\rho^2} \ l n _ { t o t f t e } \right) \beta_5 + \left( \sqrt{1-\rho^2} \ l n _ { i n v d i s c l a g } \right) \beta_6 \\
+ \left( \sqrt{1-\rho^2} \ e n r o l l m e n t \right) \beta_7 + \left( \sqrt{1-\rho^2} \ a y e a r d u m m y \right) \beta_8 \\
+ \left( \sqrt{1-\rho^2} \ m y e a r d u m m y \right) \beta_{10} + \sqrt{1-\rho^2} \epsilon_1
\]

I run two separate robust Prais-Wisten estimations for analysis of both licenses executed and invention disclosures: one with time and state fixed effects and the other with university fixed effects. I also run a robust state and time fixed effects OLS.
4. RESULTS

4.1 Startup Formation Analysis

Results from the Tobit, negative binomial, and ZINB regressions, which test Hypothesis 1, can be found in Table 3. The coefficient on $eqint$ is significant and positive across all three regression models. The number of invention disclosures a TTO received four years ago and the number of employees a TTO has are also both found to have a positive impact on startup formation, significant at the 1 percent level in all the models I employ. Interestingly, the coefficient on federal expenditures is always insignificant whereas industry funding is positive and significant at the 1 percent level. This may be due to the fact that federal funding promotes more basic research activities that do not place pressure on the university to generate commercializable products. The presence of a medical school consistently has a negative effect on startup formation, significant at the one percent level. The coefficient on $age$ is small, most likely because all three regressions employ time fixed effects. The high magnitude and significance level of the $enrollment$ coefficient suggests that university size has the largest effect on startup formation.

In order to interpret the coefficients of the Tobit model, I use the $dtobit2$ command (Wiggins 1998). The results, shown in Figure 12, indicate universities with more equity-friendly policies will generate more new firms. A TTO with average values of all explanatory variables that invests equity in 10 percent more of the startups it creates is expected to experience 1.9 percent greater startup formation the next year, significant.
at the one percent level. Given that a university will generate at least one startup, a 10 percent increase in equity intensity yields a 1.4 percent increase in conditional expected startup formation the following year.

The standard negative binomial and ZINB regressions support the results from the Tobit regression in both the magnitude of the coefficient on eqint and the significance level. I specify for the negative binomial and ZINB regression output to be returned as incident ratios, which expresses the change in the dependent variable in percentage terms. Holding all other explanatory variables constant, I find that increasing equity stakes in startups by 10 percent yields a 1.4 to 1.7 percent increase in startup formation the next year, significant at the 1 percent level.

Due to the consistency of results across the Tobit, negative binomial, and ZINB regressions, the primary analysis suggests equity financing allows for more successful technology licensing negotiations with new firms. Although the direction and significance of the coefficient on eqint is consistent with DiGregorio & Shane (2003), this thesis finds that equity-friendly policies have a smaller effect on startup formation than the two previously mentioned authors suggest. DiGregorio & Shane (2003) find universities that move from startup financing structures that involve no equity to 100 percent equity payments increase startup formation by 68 percent the ensuing year. Using this comparison, my analysis suggests that startup formation will increase by only about 14 to 20 percent.

4.2 Secondary Analysis: Survey Analysis

Before examining the effects of all four TTO policies on TTO licensing activity, I first investigate the effects of award and mentoring programs on the number of invention
disclosures a TTO receives (Hypotheses 2 & 3). The results of the robust OLS regression with state and time fixed effects, the robust Prais-Winsten regression with state and time fixed effects, and the robust Prais-Winsten estimation with university fixed effects on ln_invdis can be found in Table 4. Across all three estimations, the coefficients on ayeardummy and myeardummy are insignificant, providing strong evidence that mentoring and award programs have little impact on the number of invention disclosures a TTO receives. The Prais-Winsten transformation did a sufficient job adjusting for autocorrelation within the dataset, changing the Durbin Watson statistic from .90 to 1.67, where there is no significant evidence of first order serial correlation.

The main regressions of the secondary analysis tests Hypotheses 2 through 5, and examine how mentoring programs, innovation awards, express licenses, and iBridge network membership affect the number of licensing agreements a TTO executes. The results of the robust OLS regression with state and time fixed effects, the robust Prais-Winsten regression with state and time fixed effects, and the robust Prais-Winsten estimation with university fixed effects on ln_lcexec can be found in Table 5. The initial robust OLS regression can explain 81 percent of the variation in the model.

Results from the Prais-Winsten university fixed effects estimation, located in column 3 of Table 5, appear unreliable, most likely due to insufficient within-university variation of TTO characteristics. The coefficient on ln_invdisclag is insignificant despite the fact that invention disclosures have been consistently proven to have a positive and highly significant effect on a wide variety of TTO performance metrics, including the number of licensing agreements generated. Siegel et al. (2003) and Thursby et al. (2001) find an additional invention disclosure leads to a .69 and .78 unit increase in licensing
agreements, significant at the one percent level. From a logical perspective, invention disclosures must have a significant effect on licenses executed, as they are the main input from which licensing agreements are created. The coefficient on \( enrollment \) is also found to be insignificant in the university fixed effects regression, despite the fact that it is large and highly significant in the other two regression models. The statistical insignificance of \( \ln_{\text{invdisclag}} \) and \( enrollment \) in the Prais-Winsten university fixed effects regression suggests that the coefficients on other variables of interest in this specific estimation may be unreliable. Results from the other two regression models should be weighted much more heavily.

Innovation awards, iBridge network membership, and express licenses have no significant effect on TTO licensing activity. Express licensing programs appear to have a positive, significant effect in the initial OLS regression, but this effect disappears when first order serial correlation is controlled for. Based on email exchanges with TTO directors, the inability of award programs and iBridge network membership to increase technology transfer output is unsurprising. Many staff members stated that working with the TTO is rarely considered in tenure decisions. Innovation awards often serve to boost the visibility of the entire TTO as opposed to an individual staff member. Many innovation award programs more closely resemble a gesture of appreciation for faculty engaging in technology transfer as opposed to a prestigious award.

Consistent with the insignificant coefficient found on \( \text{ibyeardummy} \) across all 3 models, multiple TTO directors stated that although their university was an iBridge member, the network was rarely used, and staff often did not bother to update the website with newly developed inventions. Furthermore, other, potentially superior, online
advertising platforms for university inventions have been developed, including AUTM GTP and Flintbox. TTOs may be using these newer platforms as a substitute for the iBridge network. Regression results and additional survey feedback are also consistent with Thursby & Thursby (2003), who find that online networking is the least popular and effective channel for the commercialization of inventions.

The insignificant coefficient on the elyeardummy is aligned with the logic that university inventions are too unique to be packaged under one standardized contract (Association of American Universities 2007). Although Prais-Winsten regressions suggest express licenses are ineffective tools for translating a greater quantity of university innovations into commercial products, the results are far from conclusive, particularly because only 15 out of 86 universities implemented express licensing programs in the survey dataset.

Ignoring the university fixed effects Prais-Winsten estimation, implementation of a formal mentoring program increases the number of licensing agreements by 20 to 22 percent, ceteris paribus. Comparison of results from Table 5 with the insignificant relationship found between myeardummy and ln_invdis in Table 4 suggests that mentoring programs do not increase the number of invention disclosures a TTO receives, but do increase the proportion of invention disclosures that are subsequently licensed as commercial products. The guidance and vast personal networks mentors provide faculty with seem to allow TTOs to increase the magnitude of technology transfer operations despite the fact that the major input of the TTO, quantity of invention disclosures, is not changed. It is also important to note that this thesis measures only one of the proposed benefits of a mentoring program. In addition to benefiting from greater technology
transfer output, mentoring programs may also improve faculty morale, strengthen TTO staff–university faculty relations, and facilitate a more productive work environment. A case study by the Kauffman Foundation (2012) finds that there is substantial heterogeneity in TTO mentoring program structure. Further research should be directed towards investigating exactly which aspects of these mentoring programs help contribute towards more effective technology transfer efforts, particularly since most TTOs that have implemented such programs lack experience in this area. Survey results from this thesis indicate that mentoring programs are a relatively new practice, as the majority of TTOs in the 86 university dataset implemented a mentoring program in 2007 or later.

5. CONCLUSION

To the best of my knowledge, this paper is the first empirical analysis of multiple internal TTO policies. This area of research has been largely neglected despite the large uptakes rates of all four programs listed in the survey and the practical applications of potential findings. TTOs stand to experience significant gains from improving internal policies and organizational practices since most are relatively costless to change. Table 5 suggests simply organizing a system that provides individual, commercial guidance to university professors has a large effect on TTO performance, increasing licensing agreements executed by 20 to 22 percent. As suggested in the introduction of this thesis, focusing on TTO characteristics that are flexible and cheap to implement should be emphasized in future technology transfer research, as subsequent results may yield more tangible benefits to university personnel and the firms that they interact with. The AUTM possesses the ability to induce this trend in technology transfer research, as previous studies within the field of university technology transfer have been significantly
influenced by which variables have been available within their database. Information regarding TTO policies and other valuable metrics could be obtained by adding new questions to their annual survey.

Technology transfer is an area that extends far beyond the range of universities. Tech giants such as Nokia, Creative Technology Ltd, Xerox, and IBM have negotiated multiple technology licensing agreements. Researchers and corporations alike would be well advised to place greater effort in investigating the best commercialization strategies occurring in the university technology transfer sector.
Data Appendix

Variable Name: age
Variable Definition: The age of the technology transfer office. The current year subtracted by the year in which the technology transfer office was founded. Described by the AUTM 2012 Licensing Activity Survey as the “year in which your institution assigned at least 0.5 professional time employees in support of technology transfer activities” (p.4).
Unit type: numeric (integer)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:
Missing Observations: 166/2779
Range: [0, 87]
Mean: 15.66
Median: 14
Standard Deviation: 12.22
Variable Name: **ayeardummy**
Variable Definition: A dummy variable indicating whether or not the TTO acknowledged individual faculty members for outstanding technology commercialization efforts in a given year
Unit type: numeric (int)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:

Missing Observations: 1439/2779
Range: [0,1]
35 out of 83 universities implemented an innovation award program by 2012

<table>
<thead>
<tr>
<th>ayeardummy</th>
<th>Freq.</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1,109</td>
<td>82.76</td>
</tr>
<tr>
<td>1</td>
<td>231</td>
<td>17.24</td>
</tr>
</tbody>
</table>
Variable Name: **elyeardummy**
Variable Definition: A dummy variable indicating whether or not the TTO implemented an express licensing program in a given year
Unit type: numeric (int)
Source: AUTM Statt 3.4 Database
Percent of Universities in dataset with express licenses

Descriptive Statistics:

- Missing Observations: 1376/2779
- Range: [0,1]

15 out of 86 universities implemented an express licensing program by 2012

<table>
<thead>
<tr>
<th>eyleardummy</th>
<th>Freq.</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1,299</td>
<td>92.59</td>
</tr>
<tr>
<td>1</td>
<td>104</td>
<td>7.41</td>
</tr>
</tbody>
</table>
Variable Name: enrollment
Variable Definition: Undergraduate and graduate enrollment in a particular university per year
Unit type: numeric (float)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:

Missing Observations: 316/2779
Range: [495, 73378]
Mean: 20934
Median: 20024
Standard Deviation: 12594.4
Variable Name: **eqint**
Variable Definition: A proxy for the willingness of a university to take an equity stake in the startups it creates. The variable is lagged by one year. Created through dividing the number of startups generated with equity stakes by the total number of startups created per university per year (stupeq/startup).
Unit type: numeric (float)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:
Missing Observations.: 894/2779
Range: [0, 1]
Mean: .335806
Median: 0
Standard Deviation: .412261
Variable Name: fedexp
Variable Definition: Federal research funding received by a particular university in a given year
Unit type: numeric (double)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:

Missing Observations: 81/2779
Range: [0, 1532e+09]
Mean: 1.5e+08
Median: 9.1e+07
Standard Deviation: 1.7e+08
Variable Name: **i.id**  
Variable Definition: The ID code of the university. This variable is used to generate university fixed effects.  
Unit Type: String  
Source: AUTM Statt 3.4 Database  
Descriptive Statistics  
Missing Observations: 0/2779  
Unique Values: 200

Variable: **i.state**  
Variable Definition: The state in which university is located. Dummy state variables that range from 0-50 are generated so that state fixed effects can be used in regressions.  
Unit Type: String  
Source: AUTM Statt 3.4 Database  
Descriptive Statistics  
Observations: 0/2779  
Unique Values: 51 (includes Washington D.C.)

Variable: **i.year**  
Variable Definition: Year in which university statistics were recorded. Year dummy variables are employed so that time fixed effects can be used in regressions.  
Unit Type: Numeric (int)  
Source: AUTM Statt 3.4 Database  
Descriptive Statistics  
Missing Observations: 0/2779  
Range: [1991-2012]  
Unique Values: 22  
Mean: 2002.62  
Median: 2003  
Standard deviation: 5.93661
Variable Name: **ibyeardummy**
Variable Definition: A dummy variable indicating whether or not the TTO became an iBridge network member in a given year
Unit type: numeric (int)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:

Missing Observations: 1395/2779
Range: [0,1]
31/85 universities were iBridge members by 2012

<table>
<thead>
<tr>
<th>ibyeardummy</th>
<th>Freq.</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1,254</td>
<td>90.61</td>
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<tr>
<td>1</td>
<td>130</td>
<td>9.39</td>
</tr>
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</table>
Variable Name: **indexp**
Variable Definition: Quantity of industry research funding for a given university per year
Unit type: numeric (long)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:

Missing Observations: 121/2779
Range: [0, 2.657e+08]
Mean: 1.6e+07
Median: 8.8e+06
Standard Deviation: 2.3e+07
Variable Name: **invdis**

Variable Definition: The variable name stands for invention disclosures. Invention disclosures are confidential forms written by faculty that ask the TTO to evaluate whether or not some product of their research should receive patent protection. According the AUTM Tech Transfer Manual, a general rule of thumb is for every 100 invention disclosures, about 10 patents are produced.

Unit type: numeric (int)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:

Missing Observations: 13/2779
Range: [0,690]
Mean: 85.74
Median: 54
Standard Deviation: 91.71
Variable Name: **lcexec**
Variable Definition: Number of licensing agreements executed per year. Licensing agreements specify the timing and magnitude of the royalty payments and licensing fees that the firm pays in exchange for university technology. Licensing agreements are the most common way for universities to extract revenue. Licenses also specify how long the technology will be used, and the procedures that will occur in the event of a legal dispute. Unit type: numeric (int)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:

Missing Observations: 28/2779
Range: [0,287]
Mean: 24.29
Median: 12
Standard Deviation: 31.76
Variable Name: **ln_fedexp**
Variable Definition: ln(fedexp)
Unit type: numeric (double)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:

Missing Observation: 81/2779
Range: [0, 2115]
Mean: 18.16
Median: 18.32
Standard Deviation: 1.41
Variable Name: **ln_indexp**
Variable Definition: ln(indexp)
Unit type: numeric (long)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:

Missing Observations: 121/2779
Range: [0,194]
Mean: 15.83
Median: 15.9
Standard Deviation: 1.6
Variable Name: **ln_invdis**
Variable Definition: \( \ln(\text{invdis}) \)
Unit type: numeric (int)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:

- Missing Observations: 13/2779
- Range: [0, 6.54]
- Mean: 3.95
- Median: 4
- Standard Deviation: 1.1

![Histogram of ln_invdis](image)
Variable Definition: $\ln(1+\text{lcexec})$
Unit type: numeric (int)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:

Missing Observations.: 28/2779
Range: [0,5.66]
Mean: 2.26
Median: 2.56
Standard Deviation: 1.21
Variable Name: **ln_strtup**
Variable Definition: $\ln(1+\text{strtup})$
Unit type: numeric (int)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:

Missing Observations: 264/2779
Range: [0, 3.47]
Mean: .97
Median: 1.1
Standard Deviation: .79
Variable Name: \texttt{ln\_totfte}
Variable Definition: $\ln(1+\text{totfte})$
Source: AUTM Statt 3.4 Database

Descriptive Statistics:

Missing Observations: 219/2779
Range: [0, 4.38]
Mean: 1.8
Median: 1.77
Standard Deviation: .83
Variable Name: medschool
Variable Definition: Medschool = 1 if the university has a medical school. Medschool = 0 if the university does not have a medical school.
Unit type: numeric (float)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:
Missing Observations: 0/2779
Unique Values: 2 (0 or 1)

<table>
<thead>
<tr>
<th>medschool</th>
<th>Freq.</th>
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<tr>
<td>0</td>
<td>1,140</td>
<td>41.02</td>
</tr>
<tr>
<td>1</td>
<td>1,639</td>
<td>58.98</td>
</tr>
<tr>
<td>Total</td>
<td>2,779</td>
<td>100.00</td>
</tr>
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</table>
Variable Name: **myeardummy**
Variable Definition: A dummy variable indicating whether or not the TTO had a formal mentoring program in place to aid faculty in the technology commercialization process in a given year.
Unit type: numeric (int)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:
Missing Observations: 1439/2779
Range: [0,1]
45 out of 84 universities implemented a formal mentoring program by 2012

<table>
<thead>
<tr>
<th>myeardummy</th>
<th>Freq.</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1,029</td>
<td>75.11</td>
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<tr>
<td>1</td>
<td>341</td>
<td>24.89</td>
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</table>
Variable Name: **startup**
Variable Definition: The number of startups generated each year by a particular university. Djokovic and Souitaris (2008) define a university startup as, “a new company founded to exploit a piece of intellectual property within an academic institution.” University startups provide the university with a greater proportion of financial returns that stem from the licensed invention than traditional licensing agreement. Startup formation is important to analyze as it is becoming an increasingly prevalent mechanism of technology transfer, and poses unique advantages from traditional licenses.
Unit type: numeric (int)
Source: AUTM Statt 3.4 Database

Descriptive Statistics:
Missing Observations: 264/2779
Range: [0, 31]
Mean: 2.67
Median: 2
Standard Deviation: 3.43
Variable Name: **totfte**
Variable Definition: The total number of technology transfer employees per university. Includes employees with both administrative and technology licensing duties. Technology transfer office roles range from invention marketing, projecting value of inventions, accounting and legal duties.
Source: AUTM Statt 3.4 Database

**Descriptive Statistics:**

Missing Observations.: 219/2779
Range: [0,79]
Mean: 10.2087
Median: 4.86
Standard Deviation: 8.79
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Jensen, R. A., J. G. Thursby and M. C. Thursby (2003), ‘Disclosure and licensing of university inventions: ‘the best we can do with the S**T we get to work with?,’ International Journal of Industrial Organization, 21(9), 1271-1300.


Wiggins, V. (March 24, 1998). DTOBIT2: Stata module to estimate a Tobit model with marginal effects at observed censoring rate.
Data Sources


U.S. Department of Education. Institute of Education Sciences, National Center for Education Statistics.
## Tables

### TABLE 1

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Definition</th>
<th>Independent Variable</th>
<th>Definition</th>
<th>Predicted Sign</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>startup</em></td>
<td>Startups per year</td>
<td><em>eqint</em></td>
<td>Willingness of university to take startup equity stakes</td>
<td>+</td>
</tr>
<tr>
<td><em>ln_invdis</em></td>
<td>Invention disclosures per year</td>
<td><em>ayeardummy</em></td>
<td>Presence of innovation award program</td>
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<tr>
<td><em>ln_lcexec</em></td>
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<td><em>ayeardummy</em></td>
<td>Presence of innovation award program</td>
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<td>Invention disclosures per year</td>
<td><em>myeardummy</em></td>
<td>Presence of mentoring program</td>
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<td><em>ln_lcexec</em></td>
<td>Licenses executed per year</td>
<td><em>myeardummy</em></td>
<td>Presence of mentoring program</td>
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<tr>
<td><em>ln_lcexec</em></td>
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<td>Licenses executed per year</td>
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<td>Std. Dev.</td>
<td>Min</td>
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<td>(3)</td>
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<td>strtp</td>
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<td>-0.00747**</td>
<td>0.00294</td>
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<td>0.0818***</td>
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<tr>
<td><strong>ln_totfte</strong></td>
<td>0.348***</td>
<td>0.360***</td>
<td>0.356***</td>
<td>0.0630</td>
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<tr>
<td><strong>ln_invdisclag</strong></td>
<td>0.295***</td>
<td>0.316***</td>
<td>0.259***</td>
<td>0.0497</td>
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<td>.779</td>
<td>.864</td>
<td>.795</td>
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<td>1,463</td>
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Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
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<th>(1) OLS State/time FE</th>
<th>(2) Prais-Winsten State/time FE</th>
<th>(3) Prais-Winsten University FE</th>
</tr>
</thead>
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<tr>
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<td>0.0347 (0.0350)</td>
<td>0.0472 (0.0471)</td>
<td>0.0234 (0.0412)</td>
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<tr>
<td>ayeardummy</td>
<td>0.00823 (0.0374)</td>
<td>-0.00507 (0.0436)</td>
<td>0.0505 (0.0390)</td>
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<tr>
<td>ln_fedexp</td>
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<td>ln_indexp</td>
<td>0.0337* (0.0192)</td>
<td>0.00610 (0.0119)</td>
<td>-0.000534 (0.00981)</td>
</tr>
<tr>
<td>medsCHOOL</td>
<td>-0.114** (0.0450)</td>
<td>0.0161 (0.0644)</td>
<td>0.173 (0.126)</td>
</tr>
<tr>
<td>age</td>
<td>0.0153*** (0.00376)</td>
<td>0.0325** (0.00496)</td>
<td>0.0341*** (0.00460)</td>
</tr>
<tr>
<td>ln_totfte</td>
<td>0.708*** (0.0817)</td>
<td>0.574*** (0.0564)</td>
<td>0.325*** (0.0476)</td>
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<td>1,008</td>
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<td>0.833</td>
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Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
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<th>TABLE 5</th>
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<td>MODEL</td>
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<td>Prais-Winsten</td>
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<td>Time/State FE</td>
<td>Time/State FE</td>
<td>University FE</td>
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<td>VARIABLES</td>
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<td>ln lcexec</td>
<td>ln lcexec</td>
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<td>(0.0713)</td>
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<td>(0.0561)</td>
<td>(0.0635)</td>
<td>(0.0687)</td>
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<tr>
<td>elyeardummy</td>
<td>0.114*</td>
<td>0.104</td>
<td>0.0117</td>
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<td>(0.0632)</td>
<td>(0.0776)</td>
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<td>0.111**</td>
<td>0.101**</td>
<td>0.0754*</td>
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<tr>
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<td>(0.0476)</td>
<td>(0.0419)</td>
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<td>(0.0226)</td>
<td>(0.0294)</td>
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<td>-0.127</td>
<td>-0.407**</td>
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<td>(0.0106)</td>
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<td>0.550***</td>
<td>0.288***</td>
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<td>(0.0881)</td>
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<td>2.02e-05***</td>
<td>9.96e-06</td>
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<td>(2.17e-06)</td>
<td>(2.82e-06)</td>
<td>(1.89e-05)</td>
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<td>0.0880</td>
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<td>(0.0689)</td>
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<td>863</td>
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<tr>
<td>R-squared</td>
<td>0.814</td>
<td>0.684</td>
<td>0.766</td>
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Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
FIGURE 1

Total Number of Startups with University Equity Stakes

Year

FIGURE 2

Frequency Pie Chart of annual number of startups generated per university
**FIGURE 5**

White's test for Ho: homoskedasticity against Ha: unrestricted heteroskedasticity

\[
\text{chi2(43)} = 113.02 \\
\text{Prob > chi2} = 0.0000
\]

Cameron & Trivedi's decomposition of IM-test

<table>
<thead>
<tr>
<th>Source</th>
<th>chi2</th>
<th>df</th>
<th>p</th>
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<td>Skewness</td>
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<tr>
<td>Kurtosis</td>
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<td>0.0446</td>
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<td><strong>Total</strong></td>
<td><strong>207.73</strong></td>
<td><strong>52</strong></td>
<td><strong>0.0000</strong></td>
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</table>

**FIGURE 6**

[Scatter plot showing residuals vs. lag1]
FIGURE 7

Note: positive deviations show underpredictions.

FIGURE 8
FIGURE 9

FIGURE 10

. imtest, white

White's test for Ho: homoskedasticity
against Ha: unrestricted heteroskedasticity

chi2(41) = 492.40
Prob > chi2 = 0.0000

Cameron & Trivedi's decomposition of IM-test

<table>
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<tr>
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<th>p</th>
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<td>Total</td>
<td>769.33</td>
<td>50</td>
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FIGURE 11

. imtest, white

White’s test for \( H_0: \) homoskedasticity
against \( H_a: \) unrestricted heteroskedasticity

\[
\text{chi2(72)} = 227.50 \\
\text{Prob > chi2} = 0.0000
\]

Cameron & Trivedi’s decomposition of IM-test

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FIGURE 12

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