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The Impact of University Technology Transfer Offices on Faculty Consulting: Decisions by Individual Inventors.

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This study contributes to the research on industry-university interface by analysing the effect of technology transfer offices (TTO) on faculty consulting. Using fixed effects and survival analyses, I find a 25% decrease in consulting following the establishment of technology transfer offices at US universities. This effect is smaller for the researchers engaged in consulting prior to the establishment of TTO and larger for the new entrants to consulting. My findings suggest that licensing and consulting are substitutes as the sources of additional income for scientists. This result enhances our understanding of institutional change after the Bayh-Dole Act, the incentive structures of university scientists and their contribution to private sector research.

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1 Introduction

The set of incentives for pursuing research by scientists, known as 'Pasteur's Quadrant', consists of pecuniary and intrinsic rewards (Stokes, 1997; Stephan, 1996). Intrinsic rewards refer to the recognition, membership in the scientific community, and 'kick in the discovery' (Feynman & Robbins, 2005). Pecuniary motives originate in the commercial potential of research output and financial rewards for problem-solving and advisory activities.

Research/academic publishing, consulting and licensing/patenting are the main academic activities of a scientist. We can trace pecuniary and intrinsic incentives in each of these activities. However, academic publishing is largely considered the highest priority and closely tied to reputational and intrinsic benefits (Aghion et al., 2008; Thursby & Thursby, 2011), while financial incentives drive licensing and consulting activity (Thursby, Thursby, & Gupta-Mukherjee, 2007; Lach & Schankerman, 2008).

University scientists routinely make decisions on allocation of their time and resources to each of these academic activities. Recent studies find licensing and consulting to be substitutes, and both of them complement academic publishing (Jensen, Thursby, & Thursby, 2010; Fabrizio & Di Minin, 2008; Thursby & Thursby, 2011).

Scientists decide on allocation of time and resources based on a number of factors, which include institutional policies. The Bayh-Dole Act (1980) represents a milestone in cooperation between industrial sector and universities in commercializing government-funded research. It legitimised a growing practice of university patenting and licensing and significantly altered the ownership of university inventions and access to them by private firms (Mowery, Nelson, Sampat, & Ziedonis, 2004). The Bayh-Dole Act legislation enabled patenting by university faculty and changed the ways they participate in private sector research. We have evidence of a large-scale increase in university patenting and licensing after the Bayh-Dole Act (Mowery, et al., 2004). We also have evidence on the "narrowing" of the knowledge flows between universities and private firms since the Bayh-Dole Act through the reduction in diversity of sources and recipients of new university knowledge (Rosell & Agrawal, 2009).

Based on earlier findings of the post-Bayh-Dole increase in licensing and substitutionary relationship between licensing and consulting, this study asks a question: has the Bayh-Dole Act caused the reduction in private sector consulting by university researchers? I explore several aspects of this question. In particular, I examine the time trend in faculty consulting, explore the effect of the Bayh-Dole Act on consulting at the university level and at the level of individual researcher, compare the impact on all faculty to the impact on the faculty engaged in consulting, and, finally, analyze the new entry into consulting. I also propose an empirical solution to the endogeneity issues in measuring the effect of the Bayh-Dole Act. In particular, I use the establishment of Technology Transfer Offices (TTOs) at a university, which is exogenous for individual inventors, as a proxy for the Bayh-Dole effect.

This study is organized as follows. Section 2 reviews recent studies in this area. Section 3 specifies theoretical model. Section 4 provides the description of the data.

Section 5 details estimation techhniques. Section 6 presents results. Section 7 contains discussion of the findings and their importance in a broader context.

2 Literature Review

Although the Bayh-Dole Act facilitated technology transfer from universities to private sector, encouraged academic enterpreneurship (Shane, 2004) and increased employment and welfare in local communities (Hausman, 2010), active patenting and licensing by universities raised a number of concerns. One of them is a possibility of diversion from the basic research in favor of more commercially viable projects (Kenney & Patton, 2009). Several studies exploring negative effect of university licensing and patenting on production of basic research do not cite any evidence of a trade-off between patenting/licensing activities and scientific publications. Instead, these studies find that faculty perceive patenting as a minor activity compared to the traditional scientific research and publication (Agrawal & Henderson, 2002), actively patenting scientists are more productive than their non-patenting colleagues (Agrawal & Henderson, 2002), patenting by scientists usually follows a number of publications on the same topic and constitute a different medium for codifying the same invention (Azoulay, Ding, & Stuart, 2007), and revenues from licensing facilitate both basic and applied research by the same scientist (Thursby & Thursby, 2011).

Another concern related to the proliferation of patenting by universities is the impact of newly introduced intellectual property rights on knowledge flows between basic and applied research. University patents are feared to affect the openness of scientific knowledge, stifle its dissemination, reduce the speed of scientific inquiry, and limit interaction between private sector and academic researchers (Nelson, 2004). Basic science is essential for technological development in many industries (Mansfield, 1995). Contributions of basic science to applied research are well established: 41% of respondents in the Carnegie-Melon survey of R&D managers consider publications and reports sponsored by public funding important to industrial R&D, 31% said that research from university or governement lab suggested a new project and 36% claimed it helped the completion of ongoing project (Cohen, Nelson, & Walsh, 2002). The reverse flow of knowledge, from applied research to basic science, exists through cooperation between universities and industrial firms (Meyer-Krahmer & Schmoch, 1998), considerable overlap in academic and industrial communities, labor mobility and research collaboration (Lam, 2005; Zucker, Darby, & Armstrong, 2002), basic research originating from applied research[1] (Mowery, Nelson, Sampat, & Ziedonis, 2004), and large-scale basic research carried out by in-house laboratories in private sector companies like DuPont (Hounshell & Smith, 1988). University patents create disincentives for the use of scientific knowledge under intellectual property protection (Murray & Stern, 2007). This change in incentives may cause the decline in diffusion of university knowledge in the first decade after the Bayh-Dole Act (Rosell & Agrawal, 2009).

I contribute to this literature by showing that the institutional changes enacted by the Bayh-Dole Act caused the reduction in private sector consulting by university researchers. This study offers an alternative explanation for the "narrowing" of knowledge flows (Rosell & Agrawal, 2009), which I attribute to the differences between consulting and licensing in the knowledge exchange with private sector firms. I also confirm the finding that university researchers perceive consulting and licensing as substitutes (Jensen, Thursby, & Thursby, 2010). Finally, I propose using TTO establishment at a university to overcome endogeneity issues in measuring the effect of the Bayh-Dole Act.

3 Theoretical Model

The implementation of the Bayh-Dole Act in 1980 proved to be a difficult approximation of "institutional shock". Its impact was not uniform: for some universities it has legitimized practices already in place[2] (Mowery et al, 2004), while for others it took many years to create institutional structures for licensing and patenting. However, we can trace

[1] Mowery et al. (2004) cite the discovery of semiconductor material Gallium Nitride as a case of primary contribution of industrial researchers at the stages of discovery and early development

[2] IPA (Institutional Patent Agreements) are the pre-Bayh-Dole arrangements allowing universities to patent.

the effect of the Bayh-Dole Act because in every university decision to implement policies stipulated in the Bayh-Dole Act is revealed through the establishment of a Technology Transfer Office (TTO).

TTOs manage the interface between university and industry. They search for commercially promising research within university or encourage faculty to disclose such research to them. TTOs also handle patenting and licensing process, often with the help of patent attorneys. They obtain patent protection, select licensee(s), prepare and negotiate licensing agreements, coordinate engagement of faculty in the follow-up research and commercialization. TTOs, generally have no effect on scientist's research trajectory, allocation of time, or mix of activities. However, to a certain extent, TTOs can play a role of a "watchdog" over university inventions and prevent researcher from assigning the rights over the government-funded research to a private company. This arrangement does not prevent the exchange of tacit knowledge, knowledge spill-overs and minor reshuffling of funds across projects, especially if they go either direction and contribute to both government-funded and industry-funded research (Jensen, Thursby, & Thursby, 2010). TTOs rarely enforce the disclosure of university research to them. TTO are often under-staffed[3] and disclosure often depends on the faculty interest in licensing. Finally, the success of technology transfer (willingness to disclose inventions by university researchers) depends on the perception of TTO activities by faculty and on the relationships between faculty and TTO personnel (Siegel, Waldman, & Link, 2003; Owen-Smith & Powell, 2001).

I model the establishement of a TTO at a university as a supply shock in external funding, which changes the marginal utility of patenting and licensing for a university researcher. Following the result in Jensen, Thursby, and Thursby (2010)[4] I define licensing (L) and consulting (C) as substitutes. They both can be the sources of additonal funding and, at the same time, have unique intrinsic value (inventor proliferates his inventions through licensing and obtains insights from private sector research through consulting). Licensing and consulting enter researcher's utility function for additional

[3]Median number of TTO employees is 5 (Siegel et al., 2003).
[4]Theorem 2(i).

funding: $U(C, L)$. I do not specify functional form but assume some degree of substitution between licensing and consulting:

$$\frac{\partial U(C,L)}{\partial C} > 0$$
$$\frac{\partial U(C,L)}{\partial L} > 0. \tag{1}$$

If a researcher handles licensing process without TTO, the marginal utility of licensing is very low because of its high costs. The researcher have to prepare patenting documentation or hire a patent attorney, draft a licensing agreement and find a licensee or launch a start-up company. TTOs bear the cost of patenting and licensing on behalf of inventor increasing the marginal utility of licensing after the establishment of a TTO (L') making it a more time-efficient source of additional funding:

$$\frac{\partial U(C',L')}{\partial L'} > \frac{\partial U(C,L)}{\partial C} > \frac{\partial U(C,L)}{\partial L}. \tag{2}$$

The increase in the marginal utility of licensing does not affect the marginal utility of consulting. The marginal utility of licensing increases monotonically on the interval between L and L'.

$$\frac{\partial U(C,L)}{\partial C} = \frac{\partial U(\tilde{C},\tilde{L})}{\partial \tilde{C}} = \frac{\partial U(C',L')}{\partial C'}$$
$$\frac{\partial U(C,L)}{\partial L} > \frac{\partial U(\tilde{C},\tilde{L})}{\partial \tilde{L}} > \frac{\partial U(C',L')}{\partial L'} \tag{3}$$

where $\tilde{C} = C + \theta(C' - C)$ and $\tilde{L} = L + \theta(L' - L), \theta \in (0; 1)$.

Finally, I apply a limit to the number of hours researcher can devote to obtaining additional funding. The total number of hours spent on consulting and licensing stays the same because academic projects are of the highest priority to her:

$$\begin{aligned} C + L &= T, \\ C' + L' &= T. \end{aligned} \tag{4}$$

Proposition 1. Given conditions (1) - (4), the increase in the marginal utility of licensing leads to the reduction in consulting[5]:

$$C' < C. \tag{5}$$

Further, I compare two university inventors with different initial marginal utility of consulting at the time when the marginal utility of licensing changes. The cost of consulting for the researcher decreases over time through the established working relationship with a private sector firm and the cumulative nature of work carried out for his clients. On the other hand, the cost of search for consulting offers and establishing a working relationship is higher for the inventors with no consulting experience, therefore the marginal utility of consulting for an inventor with consulting experience is higher compared to the inventors with no history of consulting.:

$$\frac{\partial U(C_1, L_1)}{\partial C_1} < \frac{\partial U(C_2, L_2)}{\partial C_2}. \tag{6}$$

I assume that the difference in marginal utilities of consulting between inventors I and II remains the same after the increase in the marginal utility of licensing due to the establishment of a TTO:

$$\frac{\partial U(C_2, L_2)}{\partial C_2} - \frac{\partial U(C_1, L_1)}{\partial C_1} = \frac{\partial U(\tilde{C}_2, \tilde{L}_2)}{\partial \tilde{C}_2} - \frac{\partial U(\tilde{C}_1, \tilde{L}_1)}{\partial \tilde{C}_1} = \frac{\partial U(C_2', L_2')}{\partial C_2'} - \frac{\partial U(C_1', L_1')}{\partial C_1'}. \tag{7}$$

I also assume that increase in marginal utility of licensing is the same for inventors I and

[5] Proof is given in Appendix.

II because TTO resources are available to all faculty:

$$\frac{\partial U(C_1, L_1)}{\partial L_1} - \frac{\partial U(C'_1, L'_1)}{\partial L'_1} = \frac{\partial U(C_2, L_2)}{\partial L_2} - \frac{\partial U(C'_2, L'_2)}{\partial L'_2}. \tag{8}$$

Proposition 2. Given conditions (1), (2), (3), (4), (6), (7), (8) and Result (5), the decrease in the amount of consulting following the increase in the marginal utility of licensing is smaller for the inventor with a higher initial marginal utility of consulting[6]:

$$0 > C'_2 - C_2 > C'_1 - C_1. \tag{9}$$

4 Data

The current number of technology transfer offices established in the US universities exceeds 150. Almost all of them are members of the AUTM (Association of University Technology Managers). This organization conducts the annual survey on licensing activities of TTOs. As part of this survey, members of the AUTM report the year of TTO establishement, which I use as a division point for the pre-TTO and post-TTO periods.

The TTO foundation years are distributed over time, from the University of Wisconsin Research Foundation in 1925 to the Boise State University Office of Technology Transfer in 2009. Figure 1 displays the trend in TTO launches from 1971 to 2009. After the spike from the Bayh-Dole Act in 1980, the number of annual TTO launches is stable at five to ten new TTOs every year for the following 20 years and then drops in the early 2000's.

I identify all the patents assigned to the AUTM members using the data on the assignees from NBER Patent Data Project[7], keywords[8], as well as checking for mergers, name changes, alternative spellings and mistakes. I define the boundary of organization based on the self-identification by TTOs. For example, the University of Maryland Biotech Institute and the University of Maryland have two separate TTOs, and the University of Texas has one TTO for all campuses.

[6]Proof is given in Appendix.

[7]"Assignee" file lists 1830 assignee numbers as the US universities.

[8]For example, Stanford University will be searched for "Stanford" and "Leland".

The unit of analysis is a patent/inventor pair. I treat patents filed by inventors as revealed milestones in their careers. I use the information on patent assignee to determine university affiliation of the inventor. I define pre-TTO or post-TTO environment at a university based on the data on TTO establishment year from AUTM and patent application date.

I match patent/inventor pairs from 1971 to 2010 from the Patent Network Dataverse (Lai, D'Amour, Yu, Sun, & Fleming, 2011) to 175 unique institutions. In order to identify people with primarily academic affiliation, I keep inventors with at least half of their patents assigned to (any) university (and not private firms or other institutions). I also keep inventors affiliated with two or more universities[9] during their career if affiliations are consecutive.

Thursby, Fuller, & Thursby (2009) carry out an in-depth study of patents filed by academic researchers on behalf of for-profit companies and conclude that these patents are the result of consulting. Based on their inquiry, I indicate a consulting patent by university inventor if it is assigned to a private, for-profit company and bounded in time by patents by the same inventor assigned to the same university before and after. I apply time restrictions, i.e. university patents should be filed at least 100 days before and after consulting patent and have no more than 5 years between their filing dates. The time restrictions reduce the possibility of overlap in time between patents filed for two different organizations close in time. This design excludes or significantly reduces the cases when inventors move to a new organization. Table 1 demonstrates the data structure. Only individuals with three or more patents stay in the sample to ensure the possibility of a consulting patent between two university patents. This design allows for multiple consulting patents, including patents filed consecutively, however, in most cases, even if they repeat, consulting patents appear like isolated events.

University researchers actively patent on behalf of the government, NGOs (e.g. cancer research centers), hospitals, foreign universities, universities without membership in the AUTM and even other individuals. I delete these patents from the sample. I also exclude

[9]The groups of patents assigned to different universities are separated in time and form distinct clusters.

patents filed as a result of collaboration between universities or between university and private firm as well as patents with two or more assignees.

I fail to identify consulting patents by faculty during their tenure at 31 universities from my sample. I exclude these universities from the sample, however, empirical results hold for a full list of universities.

In the end I have a sample of 73697 university patents and 4694 consulting patents assigned to 11992 university researchers from 144 universities. Table 2 presents all the universities in the sample with corresponding number of university and consulting patents. The top 10 recipients of consulting services appear in Table 3. The sample includes patents filed from 1971 to 2010. I observe truncation due to the time lags in issuing patents after 2006. As a robustness check, I conduct analysis on the sample without truncation (patents from 1971-2005) and results hold.

The majority of university inventors in the sample do not file consulting patents. I create a sub-sample of inventors with at least one consulting patent to estimate the effect of TTOs on inventors engaged in consulting. Original sample decreases to 26997 observations for 2146 university researchers from 144 universities. Table 4 reports summary statistics for all inventors and Table 5 contains summary statistics for the inventors engaged in consulting.

Finally, I create a sample imitating hazard models to test the new entry into consulting. The exit patent of a university inventor is the unit of analysis in this dataset. I define exit patent as the first consulting patent for the inventors engaged in consulting and the last university patent in the sample for the inventors who have never pursued consulting. This sample structure enables the measurement of survival functions for the inventors in the pre-TTO environment (treated group) and post-TTO environment (control group). I treat the first consulting patent of an inventor as a hazard event[10]. I calculate the time of "survival" in days from the first patent filed by inventor to her exit patent.

[10]This dataset also has a sub-sample of 1:1 match of pre- and post-TTO inventors based on the technology class and application year of the exit patent.

5 Estimation

The goal of this study is to estimate the effect of technology transfer offices on faculty consulting. I divide the data into two time periods: before the establishment of a TTO and after the establishment of a TTO at a university. Because all the universities in my sample establish a TTO at some point in time and some had a TTO before the start of the sample in 1971[11], it is more convenient for the interpretation of results to define pre-TTO period as the treatment period and post-TTO period as the control period.

Ideally, I would like to estimate the difference in probabilities of consulting by the same reseacher at the same university in the same year in the absence and in the presence of a TTO and average it across all researchers:

$$\hat{\delta} = E(Y^1 - Y^0), \tag{10}$$

where $\hat{\delta}$ is the estimate of the treatment effect, Y^1 and Y^0 are the probabilities of consulting patent before TTO and after TTO respectively. Expectation is a linear function, therefore we can estimate the treatment effect as the difference between the average probability of consulting under pre-TTO environement and average probability of consulting under a TTO:

$$\hat{\delta} = E(Y^1) - E(Y^0), \tag{11}$$

However, at any given point in time a university either has or does not have a TTO. Therefore, I can only observe the decision of inventor to file a consulting patent under one state (pre- or post-TTO):

$$Y = (T_{uy})Y^1 + (1 - T_{uy})Y^0, \tag{12}$$

where Y is the probability of a consulting patent and indicator $T = \mathbf{1}\{preTTO\}(uy)$ for university u in year y.

In other words, we can only observe $E(Y^1|T_{uy} = 1)$ and $E(Y^0|T_{uy} = 0)$. However,

[11] 13 universities have TTOs before 1971.

we can use the available data to estimate the treatment effect under the condition of unconfoundedness,

$$E(Y^1|T_{uy}=1) - E(Y^0|T_{uy}=0) = E(Y^1) - E(Y^0) = \hat{\delta} \text{ if } T_{uy} \perp Y \tag{13}$$

Ideally, a random assignment of TTO to universities ensures the conditions of unconfoundness. In practice, the establishment of a TTO at a university is not random. It is a strategic decision by the university management caused by the increased interest in patenting and licensing. In such a way, the establishment of a TTO is endogenous to the university. Nevertheless, in this case I can treat the establishment of a TTO as exogenous because the analysis is at the level of inventor. This assumption is realistic because the decisions regarding the launch of a TTO office and its management are university-wide. Individual faculty have little influence on this decision and often are not aware of the existence of a TTO for a period of time after it started operation. These conditions allow for unconfoundedness to hold.

15.9% of inventors in the sample experienced a pre-TTO environment in their careers. This group may be different in their propensity to file consulting patents than the rest of the sample. I include an inventor in a treated group if he has ever experienced a pre-TTO environment in his career, I=$\mathbf{1}\{$preTTO$\}$(i).

To ensure the occurence of a consulting event during the inventor's tenure at a university, I designed my sample with consulting patents "squeezed" between university patents. In such a way, I force a quadratic relationship between the inventor experience (time since the first patent) and the probability of a consulting patent. I introduce two variables, $Experience$ and $Experience^2$ ($X_{pi} = Experience_{pi} + Experience^2_{pi}$) to control for the functional form. $Experience$ measures the years from the first patent of inventor i at the time of filing of patent p.

The errors on the estimates of observations grouped by inventor have serial correlation, therefore, I use cluster-robust standard errors where the patents by the same inventor form a cluster.

$$Y_{pi} = \alpha + \beta I_i + \delta T_{yu} + X_{pi}\Theta + \epsilon_i, \tag{14}$$

Possible time trends in the probability of consulting by university inventors are captured by a set of time indicators: τ_y is the average probability of filing a consulting patent in year y. The probability of a consulting patent also differs across technology classes. I include a set of indicators for technological classes: ϕ_c is the average probability of a consulting patent across technology class c.

$$Y_{pi} = \alpha + \phi_c + \tau_y + \beta I_i + \delta T_{yu} + X_{pi}\Theta + \epsilon_i, \tag{15}$$

Group indicator I_i carries a lot of heterogeneity. In other words, the characteristics of an inventor, such as university affiliation, may affect the probability of filing a consulting patent. The difference between the expected probability of consulting by treated and control inventors should be constant within pre- and post-TTO periods, $E(I^1) - E(I^0) = \beta$, otherwise parallel-trends assumption is violated: $cov(I_i, \epsilon_i) \neq 0$. If inventors at different universities have different probabilities of filing a consulting patent, then parallel-trends assumption is violated. I introduce a set of university indicators to account for the variance attributed to the university affiliation of inventor: λ_u is the average probability of consulting at university u.

$$Y_{pi} = \alpha + \phi_c + \tau_y + \lambda_u + \beta I_i + \delta T_{yu} + X_{pi}\Theta + \epsilon_i, \tag{16}$$

Due to the variation in treatment allocation across time, i.e. TTOs at different universities are founded at different points in time, I do not observe two distinct (before and after treatment) periods for the complete sample. Instead, I have TTO "shocks" in various years. Therefore, T varies across years y and universities u and is not an interaction term.

All the models above specify difference-in-difference estimation on the aggregated sample of inventors. However, even after excluding the variance associated with the application year, technology class, and university affiliation, concern that in the case of individual researchers group indicator I_i may still carry a lot of heterogeneity remains. In practice, two researchers working at the same university and filing patents in the same technology class in the same year still differ in their individual propensity to engage in consulting. I split group indicator I_i into a set of inventor fixed effects, γ_i. Fortunately for this study, some researchers switched universities during their careers[12]. A sufficient number of "movers" ensures inventor fixed effects do not absorb university fixed effects.

The data is not set as time-series: the step between inventor/patent pairs can be more than a year and there can be several inventor/patent pairs in a given year by the same inventor. In such a way, simultaneous inclusion of the first order term, $Experience$, and year fixed effects within a group of patents by inventor does not result in collinearity. Finally, I impose the functional form restriction and estimate a linear probability model (LPM),

$$Y_{pi} = \gamma_i + \phi_c + \tau_y + \lambda_u + \delta T_{yu} + X_{pi}\Theta + \epsilon_i, \tag{17}$$

where γ_i is the average probability of filing a consulting patent by inventor i. γ_i completely absorbs I_i and controls for heterogeneity in propensity to consult across inventors.

The four sets of fixed effects improve the feasibility of parallel-trends assumption, however, I still assume there is no correlation between the sets of fixed effects, e.g. the probability of consulting increases over time at the same rate across different technological classes, $(cov(\lambda_i, \epsilon_i) = 0;\ cov(\phi_i, \epsilon_i) = 0;\ cov(\gamma_i, \epsilon_i) = 0;\ cov(\tau_i, \epsilon_i) = 0)$,

$$E(Y^1) - E(Y^0) = \gamma_i + \lambda_u + \phi_c + \tau_y + \hat{\delta}(T = 1) + \bar{X}\hat{\Theta} - (\gamma_i + \lambda_u + \phi_c + \tau_y + \hat{\delta}(T = 0) + \bar{X}\hat{\Theta}) = \hat{\delta}. \tag{18}$$

Generally, there are only two concerns with the estimation of Linear Probability Models (LPM): heteroscedastic errors and the predicted values of outcome variable outside the [0;1] interval. The LPM has heteroscedastic errors because outcome variable can only take values of 1 and 0. The errors are equal $(1 - Xb)$ or $(0 - Xb)$ depending on the value of the outcome variable. In such a way, the variance of the error term is not consistent. It violates the homoscedasticity assumption: $Var(\epsilon_i) = \sigma^2, \forall i$. Heteroscedastic errors do

[12] 17.8% of researchers in my sample have worked in at least two universities.

not cause OLS estimator to be biased, however they affect its efficiency. I use robust standard errors to correct estimates in the presence of heteroscedasticity.

The second concern is that predicted values from the OLS regression cause bias because they lie outside the [0;1] interval (Horrace & Oaxaca, 2006). I check predicted values from the LPM regressions to determine their boundaries. After that I apply "trimmed" OLS estimator to correct for predicted values outside the [0;1] interval (Horrace & Oaxaca, 2006).

The majority of inventors in the sample do not have consulting patents. This fact prevents me from estimating models with inventor fixed effects using probit regression on the full sample of inventors because the values of the outcome variable for the inventors with no consulting patents is always zero. However, I can estimate the following probit model on a sample of inventors with at least one consulting patent during their career:

$$Y_{pi} = \Phi(\gamma_i + \lambda_u + \phi_c + \tau_y + \delta T_{yu} + X_{pi}\Theta + \epsilon_i), \tag{19}$$

where $\Phi(\bullet)$ is the standard normal distribution conditional on the parametres specified in the model.

In probit specification, the treatment effect is a change in the z-score between two probabilities of filing a consulting patent, which differ in one parameter, T:

$$Z_{E(Y^1)} - Z_{E(Y^0)} = \Phi(\gamma_i+\lambda_u+\phi_c+\tau_y+\delta(T=1)+X\Theta) - \Phi(\gamma_i+\lambda_u+\phi_c+\tau_y+\delta(T=0)+X\Theta) \tag{20}$$

The treatment effect in the fixed effects specification is not a coefficient on the interaction term of treatment time and group indicator[13]. In the fixed effects specification, treatment effect can be interpreted as an incremental change δ in the probabilities of an outcome in response to treatment for a particular inventor. In short, γ_i, λ_u, ϕ_c and τ_y are the four sets of indicators, which take a constant value of the average probabilities of consulting patent by inventor i, in technology class c, at university u, and in year y. Because they are constants, covariances with T are zero. Therefore, marginal effect is

[13] Detailed discussion of the interpretation of treatment effects in the non-linear models can be found in Ai & Norton (2003), Norton, Wang & Ai (2004) and Puhani (2008).

estimated as follows:

$$\frac{\partial \Phi(\bullet)}{\partial T} = \frac{\partial(\gamma_i + \lambda_u + \phi_c + \tau_y + \delta T + X\Theta)}{\partial T}\Phi'(\bullet) = \delta\Phi'(\bullet) \tag{21}$$

I estimate the average marginal effects (AME)[14]. The AME is preferred because the slope of the function is estimated at the 'true' (as measured in the sample) values of each observation and then averaged across all observations. An alternative and wide-spread technique, marginal effects at means (MEM), estimates the slope at the mean values of control variables. The majority of observations will never have all the values of control variables around their means. The indicator variables will never have their observed values at the mean. I have four sets of fixed effects and indicators for the main effect of interest, therefore, the AME is the preferred way of estimating the marginal effect of the change in the outcome in response to treatment. The AME of T is calculated as follows:

$$AME_T = \frac{1}{N}\sum_{pi=1}^{N}\frac{\partial \Phi(\bullet)}{\partial T} = \frac{1}{N}\sum_{pi=1}^{N}\frac{\partial(\gamma_i + \lambda_u + \phi_c + \tau_y + \delta T + X_{pi}\Theta)}{\partial T}\Phi'(\bullet) = \frac{1}{N}\sum_{pi=1}^{N}\delta\Phi'(\bullet), \tag{22}$$

Finally, I estimate the probability of the first consulting patent (the entry to consulting) using Cox proportional hazard model. In the context of this model I treat the filing of a consulting patent as a hazard event. First, I generate the survival functions of the control and treated groups based on the data. I calculate the aggregate probability of surviving separately for treated and control group for periods 1 through k,

$$p_k = \frac{r_k - d_k}{r_k}, \tag{23}$$

where r is the number of inventors without consulting patent at the begining of period k and d is the number of inventors filing their first consulting patent in period k. The survival function is the probability of not filing consulting patent (surviving) k or more periods from the initial date as a product of the k observed survival rates for each period:

[14] Detailed discussion of the differences between the average marginal effects (AME) and marginal effects at means (MEM) is in Bartus(2005).

$$S(k) = p_1 * p_2 * p_3 * \cdots * p_k \tag{24}$$

I compare the two survival functions for the pre-TTO and post-TTO groups using the logrank test statistic, which has χ^2 distribution with one degree of freedom:

$$\chi^2(1) = \frac{(O_{PRE} - E_{PRE})^2}{E_{PRE}} + \frac{(O_{POST} - E_{POST})^2}{E_{POST}}, \tag{25}$$

where E indicates expected events ($E = \sum_{i=1}^{k} \frac{d_i}{r_i} r$) and O indicates observed events ($O = \sum_{i=1}^{k} d_i$).

I conclude the estimation of new entry to consulting by calculating coefficient from Cox regression and hazard ratio of the probabilities of filing a consulting patent by the inventors in pre-TTO (T^1) and post-TTO (T^0)environment within t days:

$$\begin{gathered} h(t) = h_0(t) exp(\delta T), \\ HR(T^1 : T^0) = \frac{exp(T^1 \delta)}{exp(T^0 \delta)}. \end{gathered} \tag{26}$$

6 Results

I start the analysis of TTO effect on faculty consulting by examining economy-wide patenting trends in university and faculty consulting. The density graph in Figure 2 suggests that the growth rate of university patenting exceeds the overall growth in patenting around 1990. The growth rate of faculty consulting exceeds the patenting rates of universities in late 1990's. This finding counters my reasoning: the growth rate of patents from consulting increases in line with the proliferation of TTOs. This evidence, however, does not inform us about the effect of TTOs on the growth in consulting. In other words, there are three possible scenarios: 1) the observed growth in consulting patents is independent of the proliferation of TTOs and we would have observed the same trend even if no university establishes a TTO; 2) TTOs facilitate the growth in consulting patents and we would have observed less growth without TTOs; and 3) TTOs suppress the growth in consulting and we would have observed a larger growth in consulting patents otherwise.

To test this question, I estimate a number of differences-in-differences models gradually increasing restrictions and conclude with the most restrictive, the inventor fixed effects model.

Table 6 reports the results of LPM specifications on a full sample of university inventors. The outcome variable is the probability of filing a consulting patent by faculty. The main explanatory variable is an indicator taking the value of 1 for researchers if they are employed by institutions without technology transfer offices. Models from I to V allow for various degrees of heterogeneity, from less restrictive (I) corresponding to the Equation 14 to the most conservative (V) described in the Equation 17. The results in Table 6 emphasize the risks of unobserved heterogeneity and importance of parallel-trends assumption for correct estimates. The less restrictive models (I-IV) suggests no significant effect of TTO on consulting. However, as I upgrade specification with four sets of fixed effects, the coefficient estimate of TTO effect changes its sign and exhibit significant positive effect of pre-TTO environment on consulting. In other words, after controling for the average probability of a consulting patent by a given faculty as well as probabilities for a given year, university and technology class (under the assumption that all four are independent), I find the negative effect of TTO establishment on the filing of consulting patent by faculty. In less restrictive models this effect is likely to be offset by the macro-trend from Figure 2. To address the concern that the LPM predicts values outside the [0;1] interval, I apply the "trimmed" OLS estimator (Horrace & Oaxaca, 2006) to correct for the predicted values outside [0;1] interval. The magnitude of change is 1.84% - 2.27% increase in the probability of filing a consulting patent before the establishment of TTO. The mean probability of consulting patent in this sample is 6%. Based on the results from LPM and "trimmed" LPM estimators the relative decrease in probability of patenting is 23.5% - 27.4%.

The sub-sample of university inventors engaged in consulting can be estimated using both LPM and probit regressions. The results in Tables 7 and 8 are similar in sign to the estimates from the full sample, however, the relative magnitude of decrease is somewhat smaller. The absolute pre-TTO increase constitutes from 4.20% to 5.14% in the LPM and 4.50% in the probit regression. The average probabilty of consulting in this sample is 17.4%. After recalculating the increase relative to the average probability of consulting, I get a 19.4%-22.8% post-TTO reduction in the probability of filing a consulting patent for the faculty engaged in consulting according to LPM estimates. Results from probit suggest 20.5% post-TTO reduction in consulting. Lower magnitudes in this sample suggest that the effect of TTO is smaller for the researchers engaged in consulting compared to the researchers who are only considering consulting.

Figures 3 and 4 exhibit trends in probability of consulting before and after TTO. I map the trends using the coefficients on the bi-annual indicator variables five years before and after the launch of TTO (e.g. $preTTO_{-5,-4}$, $preTTO_{-3,-2}$, etc.) from the most conservative specification (with four sets of fixed effects). The baseline is any time period five years before or after the establishment of a TTO at a university. Both graphs depict a distinct drop in the probability of a consulting patent after the launch of a TTO.

Given the difference in the estimates from the two samples it is worth examining in the effect of TTO on the decision of university researcher to enter consulting. I reshape my sample to estimate the Cox proportional hazard regression. To address the concern regarding possible unobserved heterogeneity I create a smaller sample by matching exit patents of pre- and post-TTO researchers on the application year and technology class. The survival functions based on the data (Table 9 and Figure 5) suggest that pre-TTO researchers in both samples are more likely to encounter the hazard of "filing a consulting patent" at any point during 5000 days of observation. The results of Kaplan-Meier logrank test in Table 10 confirm that the survival functions of pre- and post-TTO researchers are statistically different. The pre-TTO survival function in Figure 5 is closer to the origin indicating a higher risk to file a consulting patent. Finally, I estimate the coefficients and hazard ratios using Cox proportional hazard model in Table 11. Both coefficients are positive suggesting higher incidence rate of consulting for pre-TTO researchers. The magnitude of effect in the most consrvative specification suggests the decrease in the probability of a consulting patent around 35.9% after a TTO foundation.

7 Discussion

Why is consulting important? In addition to the monetary rewards, consulting creates positive externalities from interaction with colleagues in industrial sector. Such collaborations include the exchange of knowledge which is not redundant and provide new insights for academic research. Due to the restrictions on government funding and university rights over its intellectual property, the research under consulting agreements has to be different from the primary academic activity of university researcher (Thursby et al., 2009). In such a way, consulting facilitates the interaction with knowledge which is different from scientist's primary research and encourages her to learn from the colleagues in private sector. Although the benefits of collaboration with private sector researchers are obvious to university scientists (Jensen, Thursby, & Thursby, 2010), there is no clear evidence that these collaborations will take place if pecuniary stimuli are taken away. This study provides empirical evidence suggesting that university researchers are likely to reduce the amount of consulting if there is a readily available source of additional funding in a form of licensing.

The empirical evidence in this study provides an important link between the institutional change after the Bayh-Dole Act and the shift in the incentive structures of individual researchers from consulting to licensing as sources of income. It connects the evidence on the growth in university patenting and licensing following the Bayh-Dole Act and the research on substitution effect between licensing and consulting by academics. First, my study shows that the conclusions based on economy-wide trends and even difference-in-difference estimates of aggregated samples may be misleading due to the endogeneity of the trends and the heterogeneity of choices by individuals. I believe that studying the effect at the level of individual decision-maker yields more precise estimates. I use the establishment of a technology transfer office at a university as an "institutional shock" and analyse its impact on the rate of consulting by faculty. After controlling for the unobserved heterogeneity and examining consulting decisions at the level of individual inventor, I find empirical evidence for an average decrease of 25% in faculty consulting following the establishment of a TTO. The reduction in consulting is not uniform: the effect is less salient for the faculty engaged in consulting (19%-23%) but stronger for the new entrants to consulting (36%). Although we conventionally observe a growth in the number of consulting patents by university faculty, this growth is slower than it would have been if licensing practices were not proliferated by the university TTOs.

The participation in the industry research through licensing changes the nature of knowledge exchange between university and industry researchers. In particular, the knowledge in university patent is similar, if not identical, to the knowledge in scientific publication: patents can be matched to publications (Azoulay et al., 2007; Murray et al., 2007). Moreover, universities routinely employ patent law firms to prepare patents based on the manuscripts submitted by faculty. This procedure completely detaches university scientist from the patenting process. Often university scientists take no part in the subsequent development of licensed technology: as many as one third of 124 licensing agreements for MIT patents in a study by Agrawal & Henderson (2002) do not require university inventor to follow-up the development of a licensed technology. The decrease in consulting may be responsible for the "narrowing" of knowledge flows identified by Rosell & Agrawal (2009). In case patenting and licensing replace consulting as the sources of additional income, it is important to incorporate the stimuli for the interaction with private sector researchers in licensing contracts and procedures.

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Appendix.

Proof of Propositon 1.

Apply first order Taylor approximation around $U(C', L')$:

$$U(C, L) \approx U(C', L') + \frac{\partial U(C', L')}{\partial C'}(C' - C) + \frac{\partial U(C', L')}{\partial L'}(L' - L) \tag{27}$$

Condition 4 specifies the total amount of C and L, or C' and L', equals T:

$$\begin{gathered} U(C, L) \approx U(C', L') + \frac{\partial U(\ C', L')}{\partial C'}(C' - C) + \frac{\partial U(\ C', L')}{\partial L'}(T - C' - T + C) \\ U(C, L) \approx U(C', L') + (\frac{\partial U(C', L')}{\partial C'} - \frac{\partial U(C', L')}{\partial L'})(C' - C) \end{gathered} \tag{28}$$

If marginal utility of L increases and marginal utility of C is the same, then:

$$U(C, L) < U(C', L') \tag{29}$$

Apply Conditions 1, 2 and (29) to (28):

$$C' < C. \tag{30}$$

Proof of Propositon 2.

From (30):

$$\begin{gathered} 0 > C_2' - C_2, \\ 0 > C_1' - C_1. \end{gathered} \tag{31}$$

Apply first order Taylor approximation around $U(C_2, L_2)$ and $U(C_2', L_2')$:

$$\begin{aligned} U(C_1, L_1) &\approx U(C_2, L_2) + \frac{\partial U(C_2, L_2)}{\partial C_2}(C_2 - C_1) + \frac{\partial U(C_2, L_2)}{\partial L_2}(L_2 - L_1), \\ U(C_1', L_1') &\approx U(C_2', L_2') + \frac{\partial U(C_2', L_2')}{\partial C_2'}(C_2' - C_1') + \frac{\partial U(C_2', L_2')}{\partial L_2'}(L_2' - L_1'). \end{aligned} \tag{32}$$

Condition 4 specifies the total amount of C and L, or C' and L', equals T:

$$\begin{aligned} U(C_1, L_1) &\approx U(C_2, L_2) + (\frac{\partial U(C_2, L_2)}{\partial C_2} - \frac{\partial U(C_2, L_2)}{\partial L_2})(C_2 - C_1), \\ U(C_1', L_1') &\approx U(C_2', L_2') + (\frac{\partial U(C_2', L_2')}{\partial C_2'} - \frac{\partial U(C_2', L_2')}{\partial L_2'})(C_2' - C_1'). \end{aligned} \tag{33}$$

From (33):

$$C_2 - C_1 \approx \frac{U(C_1, L_1) - U(C_2, L_2)}{\frac{\partial U(C_2, L_2)}{\partial C_2} - \frac{\partial U(C_2, L_2)}{\partial L_2}}. \tag{34}$$

From (33):

$$C_2' - C_1' \approx \frac{U(C_1', L_1') - U(C_2', L_2')}{\frac{\partial U(C_2', L_2')}{\partial C_2'} - \frac{\partial U(C_2', L_2')}{\partial L_2'}}. \tag{35}$$

Subtract (34) from (35):

$$(C_2' - C_1') - (C_2 - C_1) \approx \frac{U(C_1', L_1') - U(C_2', L_2')}{\frac{\partial U(C_2', L_2')}{\partial C_2'} - \frac{\partial U(C_2', L_2')}{\partial L_2'}} - \frac{U(C_1, L_1) - U(C_2, L_2)}{\frac{\partial U(C_2, L_2)}{\partial C_2} - \frac{\partial U(C_2, L_2)}{\partial L_2}}. \tag{36}$$

From (29):

$$\begin{aligned} U(C_1', L_1') - U(C_2', L_2') &< 0, \\ U(C_1, L_1) - U(C_2, L_2) &< 0. \end{aligned} \tag{37}$$

According to Condition 2:

$$\begin{aligned}\frac{\partial U(C_2', L_2')}{\partial C_2'} - \frac{\partial U(C_2', L_2')}{\partial L_2'} < 0, \\ \frac{\partial U(C_2, L_2)}{\partial C_2} - \frac{\partial U(C_2, L_2)}{\partial L_2} > 0.\end{aligned} \tag{38}$$

Apply (37) and (38) to (36):

$$\begin{aligned}(C_2' - C_1') - (C_2 - C_1) > 0, \\ C_2' - C_2 > C_1' - C_1.\end{aligned} \tag{39}$$

Figures and Tables

Table 1: Data Example.

patent	appdate	lastname	firstn~e	assignee
4448150	15sep1982	CATSIMPOOLAS	NICHOLAS	BOSTON UNIVERSITY
4500524	11aug1983	CATSIMPOOLAS	NICHOLAS	BOSTON UNIVERSITY
4699788	20aug1984	CATSIMPOOLAS	NICHOLAS	BOSTON UNIVERSITY
4710490	01oct1985	CATSIMPOOLAS	NICHOLAS	ANGIO MEDICAL CORPORATION
4673667	31oct1985	CATSIMPOOLAS	NICHOLAS	BOSTON UNIVERSITY
4767746	04dec1985	CATSIMPOOLAS	NICHOLAS	BOSTON UNIVERSITY
4778787	20dec1985	CATSIMPOOLAS	NICHOLAS	BOSTON UNIVERSITY
4879114	20dec1985	CATSIMPOOLAS	NICHOLAS	ANGIO MEDICAL CORPORATION
4990333	20dec1985	CATSIMPOOLAS	NICHOLAS	ANGIO MEDICAL CORPORATION
4769362	14apr1986	CATSIMPOOLAS	NICHOLAS	BOSTON UNIVERSITY
4766111	23mar1987	CATSIMPOOLAS	NICHOLAS	BOSTON UNIVERSITY
4921838	16jun1987	CATSIMPOOLAS	NICHOLAS	BOSTON UNIVERSITY
4888324	02nov1987	CATSIMPOOLAS	NICHOLAS	ANGIO MEDICAL CORPORATION
4895838	09mar1988	CATSIMPOOLAS	NICHOLAS	BOSTON UNIVERSITY
6782109	03apr2001	CATTAFESTA III	LOUIS N	UNIVERSITY OF FLORIDA

Table 2: University and Faculty Consulting Patents by Institution

University	University Patents [15]	Consulting Patents	Ratio
ALBERT EINSTEIN COLLEGE OF MEDICINE/YESHIVA UNIVERSITY	277	23	0.08
ARIZONA STATE UNIVERSITY	106	4	0.04
AUBURN UNIVERSITY	223	6	0.03
BAYLOR COLLEGE OF MEDICINE	406	44	0.11
BOSTON COLLEGE	62	1	0.02
BOSTON UNIVERSITY	380	67	0.18
BRANDEIS UNIVERSITY	134	10	0.07
BRIGHAM YOUNG UNIVERSITY	203	7	0.03
BROWN UNIVERSITY	408	60	0.15
CALIFORNIA INSTITUTE OF TECHNOLOGY	2913	192	0.07
CALIFORNIA STATE POLYTECHNIC UNIVERSITY	11	3	0.27
CARNEGIE MELLON UNIVERSITY	435	33	0.08
CASE WESTERN RESERVE UNIVERSITY	300	17	0.06
CLEMSON UNIVERSITY	236	5	0.02
COLLEGE OF WILLIAM AND MARY	10	2	0.20
COLORADO STATE UNIVERSITY	83	4	0.05
COLUMBIA UNIVERSITY	1182	56	0.05
CORNELL UNIVERSITY	1365	62	0.05
CREIGHTON UNIVERSITY	38	3	0.08
DARTMOUTH COLLEGE	148	8	0.05
DREXEL UNIVERSITY	111	5	0.05
DUKE UNIVERSITY	957	61	0.06
DUQUESNE UNIVERSITY	42	4	0.10
EAST CAROLINA UNIVERSITY	63	2	0.03
EMORY UNIVERSITY	524	35	0.07

Continued on the next page

[15]This number is not equal to the total number of patents assigned to the university. It only includes patents by inventors with three or more patents, 50% of which were assigned to (any) university.

University	University Patents	Consulting Patents	Ratio
FLORIDA STATE UNIVERSITY	412	19	0.05
GEORGETOWN UNIVERSITY	218	19	0.09
GEORGIA INSTITUTE OF TECHNOLOGY	902	57	0.06
GEORGIA STATE UNIVERSITY	117	2	0.02
HAHNEMANN UNIVERSITY	5	1	0.20
HARVARD UNIVERSITY	1022	81	0.08
INDIANA UNIVERSITY	115	3	0.03
IOWA STATE UNIVERSITY	960	22	0.02
JOHNS HOPKINS UNIVERSITY	2127	118	0.06
KANSAS STATE UNIVERSITY	193	15	0.08
KENT STATE UNIVERSITY	115	14	0.12
LEHIGH UNIVERSITY	67	5	0.07
LOUISIANA STATE UNIVERSITY	302	24	0.08
MASSACHUSETTS INSTITUTE OF TECHNOLOGY	4809	444	0.09
MEDICAL COLLEGE OF OHIO	43	2	0.05
MEDICAL COLLEGE OF WISCONSIN	110	2	0.02
MEDICAL UNIVERSITY OF OHIO AT TOLEDO	134	6	0.04
MICHIGAN STATE UNIVERSITY	1038	26	0.03
MICHIGAN TECHNOLOGICAL UNIVERSITY	121	9	0.07
MISSISSIPPI STATE UNIVERSITY	68	4	0.06
MONTANA STATE UNIVERSITY	78	4	0.05
MOUNT SINAI SCHOOL OF MEDICINE	189	17	0.09
NEW JERSEY INSTITUTE OF TECHNOLOGY	91	4	0.04
NEW MEXICO STATE UNIVERSITY	22	1	0.05
NEW YORK UNIVERSITY	690	88	0.13
NORTH CAROLINA STATE UNIVERSITY	866	64	0.07
NORTH DAKOTA STATE UNIVERSITY	41	4	0.10
NORTHEASTERN UNIVERSITY	198	6	0.03
NORTHWESTERN UNIVERSITY	620	61	0.10
OHIO STATE UNIVERSITY	562	30	0.05
OKLAHOMA STATE UNIVERSITY	90	4	0.04
OLD DOMINION UNIVERSITY	18	2	0.11
OREGON HEALTH SCIENCES UNIVERSITY	338	9	0.03
OREGON STATE UNIVERSITY	76	3	0.04
PENN STATE UNIVERSITY	958	63	0.07
PRINCETON UNIVERSITY	763	55	0.07
PURDUE UNIVERSITY	598	35	0.06
RENSSELAER POLYTECHNIC INSTITUTE	203	17	0.08
RICE UNIVERSITY	616	15	0.02
RUTGERS UNIVERSITY	480	24	0.05
SAN DIEGO STATE UNIVERSITY	5	4	0.80
ST. LOUIS UNIVERSITY	67	13	0.19
STANFORD UNIVERSITY	2486	260	0.10
STATE UNIVERSITY OF NEW YORK	1101	58	0.05
STEVENS INSTITUTE OF TECHNOLOGY	55	6	0.11
TEMPLE UNIVERSITY	181	21	0.12
TEXAS A&M UNIVERSITY	547	39	0.07
TEXAS TECH UNIVERSITY	42	5	0.12
THOMAS JEFFERSON UNIVERSITY	509	25	0.05
TUFTS UNIVERSITY	202	10	0.05
TULANE UNIVERSITY	125	16	0.13
UNIVERSITY OF AKRON	177	23	0.13
UNIVERSITY OF ALABAMA	544	22	0.04
UNIVERSITY OF ARIZONA	357	24	0.07
UNIVERSITY OF ARKANSAS	388	15	0.04

Continued on the next page

University	University Patents	Consulting Patents	Ratio
UNIVERSITY OF ARKANSAS FOR MEDICAL SCIENCES	24	2	0.08
UNIVERSITY OF CA SYSTEM	9176	494	0.05
UNIVERSITY OF CENTRAL FLORIDA	518	24	0.05
UNIVERSITY OF CHICAGO	604	15	0.02
UNIVERSITY OF CINCINNATI	157	15	0.10
UNIVERSITY OF COLORADO	409	59	0.14
UNIVERSITY OF CONNECTICUT	286	21	0.07
UNIVERSITY OF DAYTON	96	1	0.01
UNIVERSITY OF DELAWARE	207	13	0.06
UNIVERSITY OF FLORIDA	1362	77	0.06
UNIVERSITY OF GEORGIA	327	26	0.08
UNIVERSITY OF HAWAII	113	3	0.03
UNIVERSITY OF HOUSTON	189	4	0.02
UNIVERSITY OF IDAHO	94	4	0.04
UNIVERSITY OF ILLINOIS	903	46	0.05
UNIVERSITY OF IOWA	601	16	0.03
UNIVERSITY OF KANSAS	164	7	0.04
UNIVERSITY OF KENTUCKY	481	16	0.03
UNIVERSITY OF LOUISVILLE	22	1	0.05
UNIVERSITY OF MAINE	22	1	0.05
UNIVERSITY OF MARYLAND	409	9	0.02
UNIVERSITY OF MARYLAND BIOTECH INSTITUTE	81	2	0.02
UNIVERSITY OF MASSACHUSETTS	32	1	0.03
UNIVERSITY OF MASSACHUSETTS MEDICAL CENTER	347	25	0.07
UNIVERSITY OF MIAMI	182	4	0.02
UNIVERSITY OF MICHIGAN	1531	101	0.07
UNIVERSITY OF MINNESOTA	1117	49	0.04
UNIVERSITY OF MISSISSIPPI	70	5	0.07
UNIVERSITY OF MISSOURI	372	37	0.10
UNIVERSITY OF MONTANA	24	1	0.04
UNIVERSITY OF NEBRASKA	313	12	0.04
UNIVERSITY OF NEVADA	34	2	0.06
UNIVERSITY OF NEW MEXICO	261	6	0.02
UNIVERSITY OF NEW ORLEANS	29	1	0.03
UNIVERSITY OF NORTH CAROLINA	751	64	0.09
UNIVERSITY OF NORTH TEXAS	34	1	0.03
UNIVERSITY OF OKLAHOMA	272	14	0.05
UNIVERSITY OF OREGON	84	2	0.02
UNIVERSITY OF PENNSYLVANIA	1210	81	0.07
UNIVERSITY OF PITTSBURGH	737	38	0.05
UNIVERSITY OF ROCHESTER	303	9	0.03
UNIVERSITY OF SOUTH ALABAMA	21	1	0.05
UNIVERSITY OF SOUTH CAROLINA	86	2	0.02
UNIVERSITY OF SOUTH FLORIDA	438	14	0.03
UNIVERSITY OF SOUTHERN CALIFORNIA	777	66	0.08
UNIVERSITY OF TENNESSEE	425	22	0.05
UNIVERSITY OF TEXAS SYSTEM	2671	220	0.08
UNIVERSITY OF TULSA	9	2	0.22
UNIVERSITY OF UTAH	865	88	0.10
UNIVERSITY OF VERMONT	90	9	0.10
UNIVERSITY OF VIRGINIA	469	18	0.04
UNIVERSITY OF WASHINGTON	1069	78	0.07
UNIVERSITY OF WISCONSIN	2494	95	0.04
UNIVERSITY OF WYOMING	57	8	0.14
UTAH STATE UNIVERSITY	87	4	0.05
Continued on the next page			

University	University Patents	Consulting Patents	Ratio
VANDERBILT UNIVERSITY	292	11	0.04
VIRGINIA COMMONWEALTH UNIVERSITY	144	12	0.08
VIRGINIA POLYTECHNIC INSTITUTE	301	23	0.08
WAKE FOREST UNIVERSITY	182	4	0.02
WASHINGTON UNIVERSITY ST. LOUIS	556	18	0.03
WAYNE STATE UNIVERSITY	285	23	0.08
WEST VIRGINIA UNIVERSITY	59	2	0.03
WESTERN KENTUCKY UNIVERSITY	2	1	0.50
YALE UNIVERSITY	592	30	0.05
Total Number of Patents and Average Ratio	73697	4694	0.07

Table 3: Top 10 Assignees of Consulting Patents

Name	Number of Consulting Patents
XEROX CORP	72
CENTOCOR INC	59
IBM	39
UNIVERSAL DISPLAY CORPORATION	39
PHARMACYCLICS INC	37
GERON CORP	36
GENERAL ELECTRIC	34
OMNIGUIDE COMMUNICATIONS	33
AMBERGEN INC	30
HEWLETT PACKARD	26

Table 4: Summary Statistics (Full Sample)

Variable	Observations	Mean	Sd	Min	Max
Application Year	78391	1997.51	6.75	1971	2010
TTO Year	78391	1977.42	17.00	1925	2005
University Patent (indicator)	78391	0.94	0.237	0	1
Consulting Patent (indicator)	78391	0.06	0.237	0	1
Patent count, by Inventor	78391	14.08	23.247	2	274
Experience (Years from First Patent)	78391	6.660	6.793	0	43
Percent of University Patents by Inventor (cutoff at 0.5)	78391	0.864	0.158	0.5	1
Pre-TTO	78391	0.064	0.244	0	1
Treated (inventors who have filed a patent in the pre-TTO environment)	78391	0.159	0.365	0	1

Table 5: Summary Statistics (Inventors with Consulting Patents Only)

Variable	Observations	Mean	Sd	Min	Max
Application Year	26997	1997.52	6.559	1971	2010
TTO Year	26997	1976.69	17.17	1925	2005
University Patent (indicator)	26997	0.826	0.379	0	1
Consulting Patent (indicator)	26997	0.174	0.379	0	1
Patent count, by Inventor	26997	24.446	34.964	2	274
Experience (Years from First Patent)	26997	9.195	7.548	0	43
Percent of University Patents by Inventor (cutoff at 0.5)	26997	0.753	0.139	0.5	0.993
Pre-TTO	26997	0.055	0.228	0	1
Treated (inventors who have filed a patent in the pre-TTO environment)	26997	0.190	0.392	0	1

Figure 1: The Number of New Technology Transfer Offices by Year.

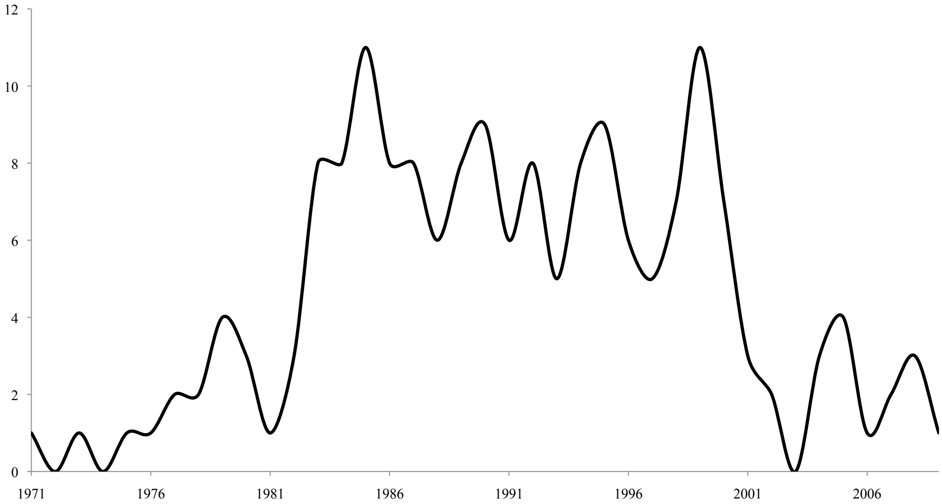

Figure 2: Density Plot

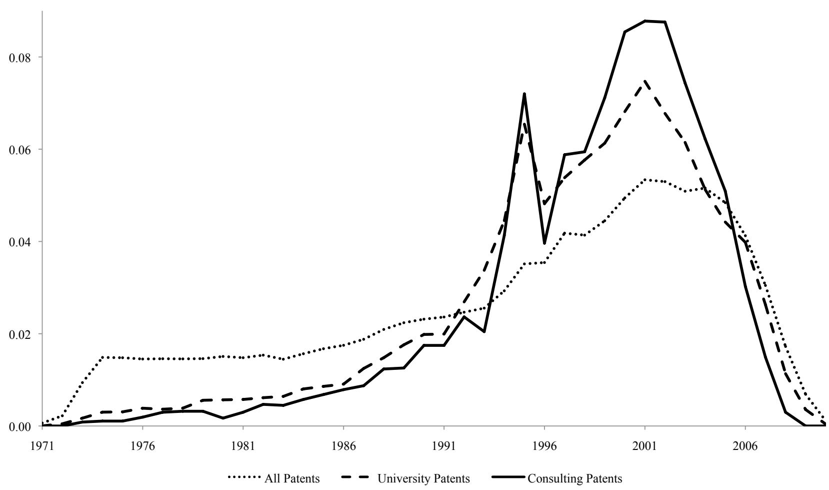

Table 6: The Effect of TTO on Faculty Consulting (All University Inventors), Linear Probability Model (LPM)

	I		II		III		IV		V	
Probability of Consulting	LPM	LPM (trimmed)	LPM	LPM (trimmed)	LPM	LPM (trimmed)	LPM	LPM (trimmed)	LPM	LPM (trimmed)
treated	-0.00591	-0.00544	-0.00196	-0.00189	-0.00303	-0.00345	-0.000391	-0.00500	Absorbed by	
	(0.00610)	(0.00611)	(0.00593)	(0.00600)	(0.00604)	(0.00622)	(0.00610)	(0.00649)	inventor fixed effects	
preTTO	-0.000140	-0.000440	-0.00242	-0.00273	0.00343	0.00328	0.00501	0.00855	0.0184*	0.0227*
	(0.00684)	(0.00684)	(0.00669)	(0.00686)	(0.00667)	(0.00687)	(0.00673)	(0.00751)	(0.00772)	(0.00982)
exp	0.00785***	0.00828***	0.00786***	0.00844***	0.00796***	0.00904***	0.00780***	0.00924***	0.00857***	0.00957***
	(0.000648)	(0.000542)	(0.000635)	(0.000538)	(0.000652)	(0.000551)	(0.000619)	(0.000562)	(0.000892)	(0.00113)
exp2	-0.000222***	-0.000246***	-0.000227***	-0.000259***	-0.000223***	-0.000287***	-0.000222***	-0.000292***	-0.000242***	-0.000289***
	(0.0000320)	(0.0000259)	(0.0000313)	(0.0000256)	(0.0000316)	(0.0000249)	(0.0000292)	(0.0000245)	(0.0000302)	(0.0000309)
Tech Class Effects (c)	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects (y)	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
University Effects (u)	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Individual Inventor Effects (i)	No	No	No	No	No	No	No	No	Yes	Yes
N	78391	78306	78391	75654	78391	73863	78391	69112	78391	51764
AIC	-3842.2	-3994.0	-5487.7	-4690.0	-5669.9	-4830.7	-6079.1	-2382.1	-22597.0	-16675.9
R-sq	0.00980	0.0100	0.0384	0.0339	0.0416	0.0371	0.0500	0.0463	0.0429	0.0452

Standard errors in parentheses
Standard errors are robust and clustered on inventor
+ p<0.1, * p<0.05, ** p<0.01 *** p< 0.001
R-sq determines the explained variance within group, university, technology class, and application year.

Table 7: The Effect of TTO on Faculty Consulting (University Inventors Engaged in Consulting), Linear Probability Model (LPM)

	I		II		III		IV		V	
Probability of Consulting	LPM	LPM (trimmed)	LPM	LPM (trimmed)	LPM	LPM (trimmed)	LPM	LPM (trimmed)	LPM	LPM (trimmed)
treated	-0.0260*	-0.0254*	-0.0143	-0.0196+	-0.00538	-0.0115	-0.00422	-0.00516	Absorbed by	
	(0.0115)	(0.0116)	(0.0106)	(0.0107)	(0.0109)	(0.0113)	(0.0105)	(0.0110)	inventor fixed effects	
preTTO	-0.0112	-0.0115	-0.0103	-0.0156	0.0137	0.0119	0.0207	0.0174	0.0420*	0.0514*
	(0.0152)	(0.0152)	(0.0153)	(0.0147)	(0.0154)	(0.0153)	(0.0155)	(0.0170)	(0.0188)	(0.0226)
exp	0.00524***	0.00616***	0.00549***	0.00660***	0.00402**	0.00582***	0.00448**	0.00680***	0.0172***	0.0212***
	(0.00137)	(0.00120)	(0.00131)	(0.00118)	(0.00138)	(0.00126)	(0.00137)	(0.00118)	(0.00210)	(0.00243)
exp2	-0.000241***	-0.000286***	-0.000243***	-0.000292***	-0.000205***	-0.000285***	-0.000227***	-0.000321***	-0.000508***	-0.000713***
	(0.0000552)	(0.0000468)	(0.0000521)	(0.0000450)	(0.0000550)	(0.0000501)	(0.0000544)	(0.0000454)	(0.0000714)	(0.0000626)
Tech Class Effects (c)	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects (y)	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
University Effects (u)	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Individual Inventor Effects (i)	No	No	No	No	No	No	No	No	Yes	Yes
N	26997	26912	26997	26188	26997	25131	26997	24639	26997	19120
AIC	24150.7	24066.1	23212.4	22753.8	23058.0	21957.7	22995.7	21909.7	20410.9	15271.2
R-sq	0.00323	0.00368	0.0555	0.0536	0.0635	0.0633	0.0743	0.0734	0.0791	0.0733

Standard errors in parentheses
Standard errors are robust and clustered on inventor
+ p<0.1, * p<0.05, ** p<0.01 *** p< 0.001
R-sq determines the explained variance within group, university, technology class, and application year.

Table 8: The Effect of TTO on Faculty Consulting (University Inventors Engaged in Consulting), Probit Regression and Average Marginal Effects (AME)

	I		II		III		IV		V	
Probability of Consulting	Probit	AME	Probit	AME	Probit	AME	Probit	AME	Probit	AME
treated	-0.104*	-0.0259*	-0.0629	-0.0151	-0.0238	-0.00574	-0.0243	-0.00578	Absorbed by the inventor fixed effects	
	(0.0475)	(0.0112)	(0.0450)	(0.0105)	(0.0468)	(0.0112)	(0.0447)	(0.0105)		
preTTO	-0.0484	-0.0121	-0.0537	-0.0129	0.0558	0.0138	0.0732	0.0180	0.196+	0.0450+
	(0.0653)	(0.0160)	(0.0671)	(0.0157)	(0.0686)	(0.0175)	(0.0706)	(0.0180)	(0.104)	(0.0256)
exp	0.0231***	0.00592***	0.0253***	0.00620***	0.0206***	0.00501***	0.0231***	0.00555***	0.0460*	0.00989*
	(0.00587)	(0.00151)	(0.00588)	(0.00145)	(0.00605)	(0.00148)	(0.00606)	(0.00146)	(0.0194)	(0.00417)
exp2	-0.00107***	-0.000275***	-0.00114***	-0.000279***	-0.00104***	-0.000252***	-0.00116***	-0.000277***	-0.00310***	-0.000667***
	(0.000261)	(0.0000663)	(0.000257)	(0.0000627)	(0.000263)	(0.0000639)	(0.000259)	(0.0000620)	(0.000409)	(0.0000871)
Tech Class Effects (c)	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects (y)	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
University Effects (u)	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Individual Inventor Effects (i)	No	No	No	No	No	No	No	No	Yes	Yes
N	26997	26997	26997	26997	26997	26997	26997	26997	26997	26997
AIC	24858.7	24856.7	24301.2	24301.2	24151.7	24151.7	24105.3	24105.3	22460.8	22480.8
Pseudo R-sq	0.0038	0.0038	0.0446	0.0446	0.0534	0.0534	0.0654	0.0654	0.1632	0.1632

Standard errors in parentheses
Standard errors are robust and clustered on inventor
+ p<0.1, * p<0.05, ** p<0.01 *** p< 0.001
Pseudo R-sq determines the explained variance within group, university, technology class, and application year.

Figure 3: The Probability of Consulting Before and After TTO.

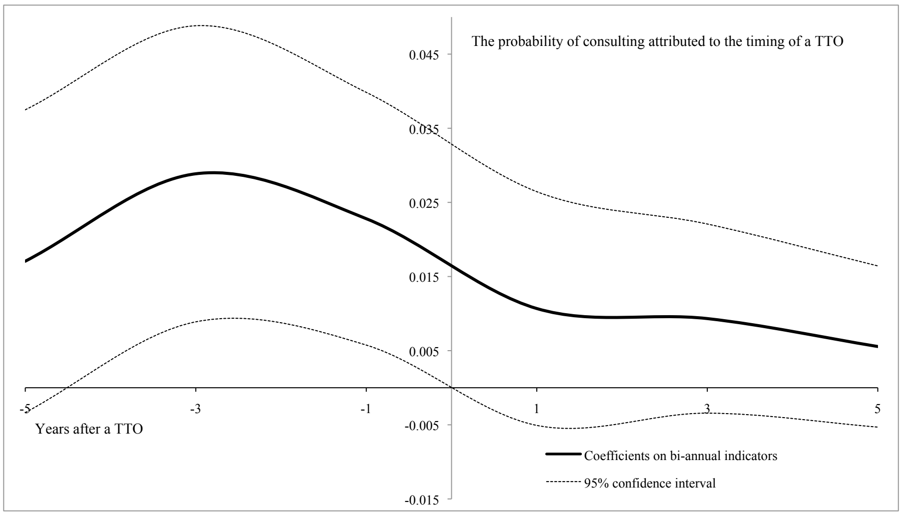

Figure 4: The Probability of Consulting Before and After TTO (Faculty with Consulting Patents)

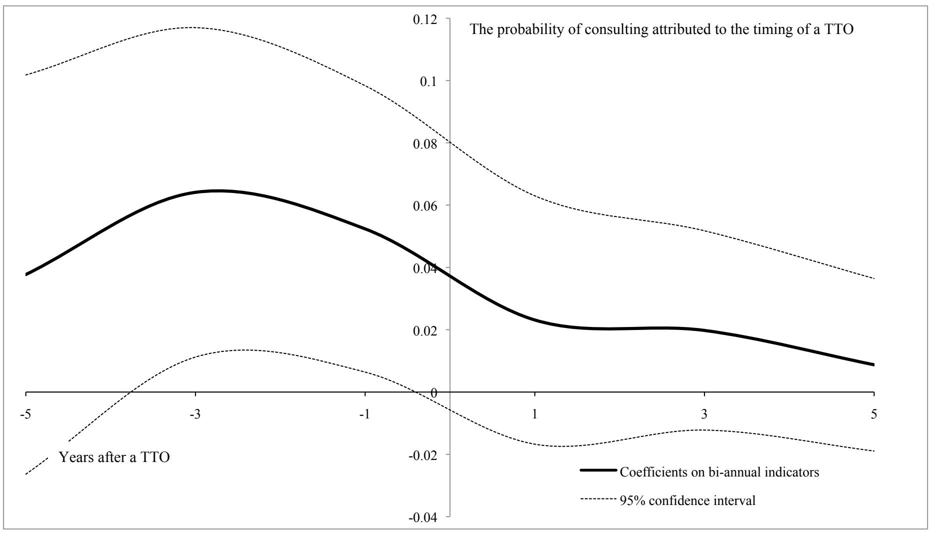

Table 9: Survival Function on the Hazard of Filing Consulting Patent by Faculty before TTO (treated group) and after TTO (control group).

Full Sample			1:1 Match on Tech Class of Exit Patent			1:1 Match on Tech Class and Application Year of Exit Patent		
Days	Control	Treated	Days	Control	Treated	Days	Control	Treated
1	1.000	1.000	7	1.000	1.000	7	1.000	1.000
625	0.951	0.9091	631	0.9289	0.9093	627	0.9451	0.9083
1249	0.8972	0.8026	1255	0.8627	0.8081	1247	0.8837	0.8474
1873	0.8431	0.7046	1879	0.7943	0.7023	1867	0.8222	0.7657
2497	0.7943	0.6336	2503	0.6943	0.642	2487	0.7612	0.6838
3121	0.7553	0.5113	3127	0.6407	0.5176	3107	0.6821	0.5428
3745	0.6971	0.4285	3751	0.5578	0.4338	3727	0.5773	0.4824
4369	0.6349	0.3794	4375	0.4184	0.3841	4347	0.5045	0.402
4993	0.3346	0.1897	4999	.	0.192	4967	0.3604	.

Table 10: The Log-rank Test for the equality of the survival functions for control and treated groups.

Full Sample			1:1 Match on the Tech Class of Exit Patent			1:1 Match on the Tech Class and Application Year of Exit Patent		
preTTO	Events observed	Events expected	preTTO	Events observed	Events expected	preTTO	Events observed	Events expected
0	1996	2075.57	0	125	146.21	0	48	60.11
1	140	60.43	1	134	112.79	1	63	50.89
Total	2136	2136		259	259		111	111
Obs	11889	11889		978	978		474	474
$\chi^2(1)$	108.29			7.20			5.40	
Pr$>\chi^2$	0.0000			0.0073			0.0202	

Figure 5: Kaplan-Meier Survival Estimates

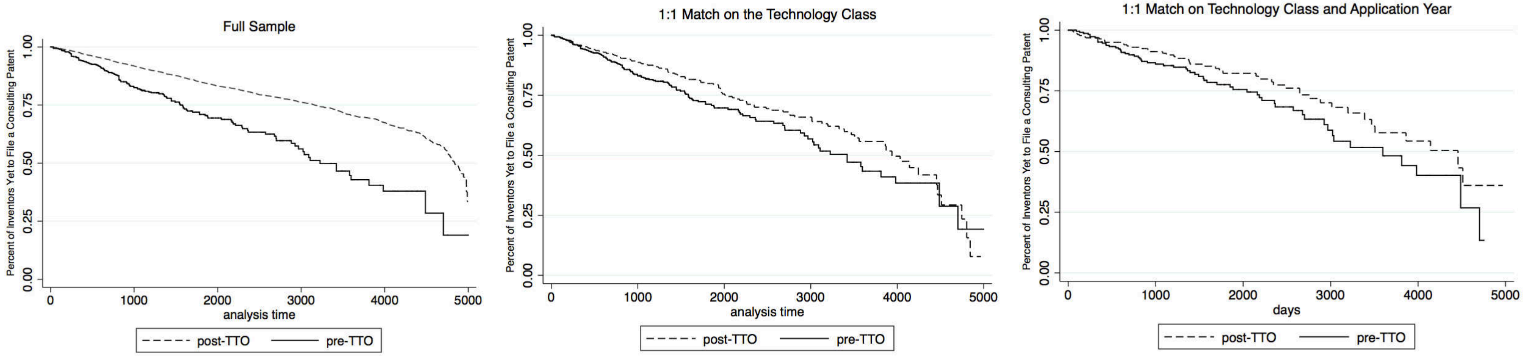

Table 11: Cox proportional hazard regression.

pre-TTO	Full Sample	1:1 Match on the Tech Class of Exit Patent	1:1 Match on the Tech Class and Application Year of Exit Patent
Coefficient	0.885***	0.335***	0.445**
	(0.085)	(0.124)	(0.191)
Hazard Ratio	2.423***	1.398***	1.560**
	(0.206)	(0.174)	(0.298)
Obs	11889	978	474
Pr> χ^2	0.000	0.0071	0.0198

Standard errors in parentheses
Standard errors are robust
+ p<0.1, * p<0.05, ** p<0.01 *** p<0.001