A career in innovation: serial faculty inventors

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Abstract: This paper explores the invention patterns of 349 science and engineering faculty in US universities. The work builds upon existing life cycle models to empirically test the idea that academic consulting is more likely to occur later in the career span of such researchers. We also test for the impact of university environmental factors such as the presence of technology transfer offices. Using a novel transition probability method paired with econometric modelling we find strong support for academic consulting to yield staying power and to occur later in a faculty member’s career. We also find support for licensing revenues to encourage university research while the presence of a transfer office was not significant in our analysis.

Keywords: academic inventors; faculty consulting; human capital.


Biographical notes: Anne W. Fuller is an Associate Professor of Strategy, Innovation and Entrepreneurship. Her research explores the commercialisation of university research as well as global R&D. She brings over 20 years of high technology industry experience into her research and classrooms.

1 Introduction

Prior research shows the existence of a phenomenon of faculty inventor patents that are assigned to firms rather than the employing university. When searched by inventor name, rather than university assignment, 33% of patents with at least one faculty member as an inventor are not assigned to the university either solely or jointly with another entity. These patents may be assigned to firms, governments, or unassigned (Link et al., 2007; Markman et al., 2008; Thursby et al., 2009). For universities to maximise the value of the intellectual property created by their faculty, they must understand the factors that influence this behaviour. The primary goal of this research paper is to shed light on the inventor, institutional and sequential characteristics that are significant in the assignment patterns of faculty invented intellectual property.

We posit that there are different types of knowledge used in generating these inventions whether it is for university research or consulting. This intellectual human capital is framed by the underlying research questions of interest to the faculty member. As we investigate patterns of assignment, we remember that the assigned patent is merely an output proxy. Our real interest is in how the faculty member selects a type of research
project into which he is going to invest his time. To explore this question, we follow the full patenting history of 349 academic scientists and engineers. Exploring academics that have shown the willingness to make a dichotomous decision in inventing both at the university and in an industrial setting provides a basis for studying the factors that influenced that decision.

What has been missing to this point in the academic invention discussion is a career level view of faculty research. This exploration builds upon prior work in life cycle behaviour, university technology transfer, and the economics of human capital investment. Though classic work such as Gary Becker’s (1962) show that switching costs of specific human capital are higher than for more general human capital and newer models address individual decisions on academic activities (Jensen et al., 2010; Thursby et al., 2007), there is more limited work on career decisions. Levin and Stephan (1991) theorise that academic researchers will invest in future oriented earnings even to at time sacrificing current income. We are able to update and test their model for insights on expected academic innovation behaviours.

We tested whether the decision to pursue academic consulting followed existing life cycle models and find several contributions to the field. First, we determined that, as predicted, consulting does increase in likelihood as the faculty member ages in her career. We use a career level sample of academic inventors to confirm results that a higher revenue sharing percentage, will tend to increase the likelihood of university research choices by the inventing faculty. We also find that faculty in public universities are more likely to consult than those at private universities. Finally, since the research pursued over a career cannot be considered a collection of isolated decisions, we tested them as a series of sequential decisions. Using methods borrowed from decision sciences, we found a high degree of correlation among; prior, current and subsequent research decisions and further that industry related inventions are ‘stickier’ than university ones. These findings have policy implications for both universities and firms working with research faculty.

2 Theory development

2.1 Life cycle hypothesis

Science and engineering faculty in major research universities make many choices throughout their career on how to invest their time and efforts. Academics participate in three conventional areas of university evaluation: research, teaching and service. While there can be heterogeneity in each of these areas, our focus here will be on faculty research. In particular, we are interested in the types of research faculty perform at research 1 universities (per the National Research Council, 1995). We explore choices between university research and consulting work with scientific merit (Mansfield, 1995).

Exploring the possible long-term factors effecting faculty industrial consulting, we build from prior work on academic life cycle models. Levin and Stephan (1991) model overall research productivity of university faculty members. They incorporate a ‘love of solving puzzles’ aspect in the model which does not change over time. Prior human capital models, based on an expected life cycle, show people invest in learning early and thus forego current earnings to build additional future earnings. This investment-motivated model predicts that academics expend effort today on research in anticipation of future earnings. As in typical life cycle production functions, the
accumulation of research (or earnings in the labour economic tradition) increases with time. The longitudinal rate of growth decreases and eventually results in an overall decline of production (c.f. Ben-Porath, 1967).

We utilise the theoretical framework of research on the impact of university licensing of academic research (Thursby et al., 2007). The model adapted here explores the idea that academic scientists choose to allocate their time between several activities. In the Thursby et al.’s model (hereafter, TTGM) the choices are research (basic and/or applied), market goods, leisure and the net present value of retirement assets (where teaching is considered a fixed load and therefore invariant over time).

As in Jensen et al. (2010) we examine in consulting which generates new knowledge (in contrast to say expert witness testimony). We limit our discussion of academic consulting to industry or firm related matters. We, as they, therefore exploit firm assigned patents as a measure of industrial consulting activity. With this restriction, we do not provide insights into consulting at the federal national laboratories for example. Nonetheless some initial findings based on cross sectional survey data indicate that tenured and older faculty are more likely to patent with industry (Allen et al., 2007). The authors note as an area of future research: “propensity of academics to partner and to patent with industry should examine the lifecycle of such a relationship” [Allen et al., (2007), p.949]. We build from prior work that patents wit faculty member inventors which are assigned to firms, are most often generated from academic consulting (including entrepreneurship) with scientific merit (Jensen et al., 2010; Thursby et al., 2009). Therefore, the study of the career span of faculty patent assignment patterns is an appropriate method for evaluating underlying academic consulting and university research efforts.

We investigate the relationship between university research and consulting. In this case, university research (whether applied or basic in nature, as long as it occurs in the university lab) is equivalent to basic research in the TTGM models. Consulting then becomes their applied effort. Following the TTGM complements model, the investment in university research is highest early in the career and tapers off towards the end of the career. The model aligns with the human capital model of early investment in knowledge due to expected future earnings leveraged on this knowledge stock (Becker, 1962; Ben-Porath, 1967). In contrast, consulting starts at a lower level and increases throughout the academic career. This is due to incentives for current income increasing since there is a shorter window for future earnings.

Many life cycle models study the total production functions of wages or knowledge and predict a declining rate of growth over the life. In our application, we are interested in the pattern of types of research rather than the total level of knowledge produced. Therefore, we are interested in the relative production of knowledge between university research and consulting. Since consulting can have a deferred compensation component (stock options or firm equity) it should have similarities to the applied research with licensing in the TTGM complements model. Thus, we expect the ratio of consulting to university research to keep increasing during the career.

Hypothesis 1 The ratio of academic consulting relative to university research will tend to increase with years as a faculty member.
2.2 University context hypothesis

In the previous section, we explored how individual life cycles would impact the probability of research decisions regarding university research versus academic consulting. Another major consideration is the environment of the employing university. Universities are known to be heterogeneous in many aspects including interest in commercialising research (Ding and Choi, 2011; Nerkar and Shane, 2003). Universities often utilise technology transfer offices (TTOs) to assist in university-industry transfers. Formal transfer mechanisms and institutions such as TTOs and business incubators are established by the university to help in the management of commercialisation activities and also can help capture financial returns for the university (Link et al., 2007).

Universities also vary in their royalty policies for technology licensed out to firms. Higher shares of royalty income to the faculty inventor increase the percentage of patents going to the university (Jensen et al., 2010; Thursby et al., 2009). One of the reasons faculties tend to prefer their university research to research for companies is the autonomy to determine their own research agenda (Aghion et al., 2008).

University TTOs have been studied extensively since becoming widespread across major US campuses during the 1980s and early 1990s. The exact duties of the TTO can vary but involves working with faculty on submitting disclosures and finding appropriate industry incumbents or new firms to further develop the technology for the marketplace. Established TTO’s help firms evaluate technologies with a better chance of commercial success and facilitate contracts between the university, faculty and firms (Hoppe and Ozdenoren, 2005; Macho-Stadler et al., 2007). The TTO is chartered to produce formal patent, licensing and other contractual agreements under the auspices of the university (Link et al., 2007). In this regard, one expects universities with a TTO would have a higher likelihood of university assigned patents. We therefore posit that after the establishment of a TTO at the home institution, we will see greater likelihood of university focused research.

Additional complementary assets such as university business incubators and university science parks are becoming more commonplace in US university settings. Controlling for these additional organisations will help delineate the value of each of these structures for faculty research decisions.

Hypothesis 2a University policies of higher license revenue sharing will increase university research relative to academic consulting.

Hypothesis 2b University investments in TTO establishment will increase university research relative to academic consulting.

2.3 Human capital investment hypothesis – general vs specific knowledge

If the hypotheses stemming from the two previous sections were confirmed, faculty members early in their careers would overwhelmingly assign patents to universities. Then, an increasing percentage would be assigned to firms later in a career. Also, faculty members at universities with TTO’s and relatively higher license revenue sharing would produce a higher percentage of patents assigned to the university regardless of age.

What is missing thus far in our discussion is a better understanding of the type of knowledge inherent in university research versus consulting. In seeking this explanation, we turn to the theoretical framework put forward in Gary Becker’s (1962) foundational
work on human capital. Becker explores the economic conditions that would cause a firm to make a human capital investment in either ‘general’ knowledge or ‘specific’ knowledge. Within this framework, ‘specific’ knowledge results in increased productivity returns only to the firm that makes the investment (the knowledge is not transferrable). Conversely, ‘general’ knowledge is completely transferrable and as such a firm will only make such an investment if the recipient of the knowledge is willing to ‘pay’ for the knowledge in the form of reduced costs (Becker, 1962).

In our application, a research decision that results in a university assigned patent represents a decision to invest in ‘general’ knowledge while a firm assigned patent represents an investment in ‘specific’ knowledge. The key difference in our context is the faculty member’s expected trade-off between current and future rewards. Under the human capital model, an employee must be willing to bear the costs of the ‘general training’ since the employer cannot be assured of non-transferable productivity gains as the result of the investment. Here, these results in the faculty member foregoing direct compensation (consulting fees) in the expectation of increased future earnings resulting from the general knowledge produced. These returns may be in the form of increased academic stature (and earlier promotion to full professor) licensing revenue from the university’s TTO or follows on work (either general or specific) stemming from the current project decision.

On the ‘specific knowledge’ of firm consulting, the faculty member receives compensation for a direct application of specific knowledge to answer the firm’s question – and thereby allow the firm to collect the downstream rewards in exchange for faculty compensation in excess of faculty salary (from the academic perspective). However, we argue that academics are paid in part to continue accrual of general knowledge and therefore provide an ideal opportunity for choices made about general or firm specific human capital. Simply put, the faculty member, having made the decision to invest her time in research (following the TTGM model), now chooses between an investment in ‘general’ knowledge (university research) and ‘specific’ knowledge (consulting).

Basically, to choose to invest in general knowledge (aka university assignment), the faculty member believes that either the problem can be solved in such a fashion that the breath of the claims will recoup benefits greater than she would reap from the specific consulting engagement. Alternatively, she may believe that using TTO resources, her gain from licensing the same invention possibly to multiple firms, would exceed the consulting returns. The gamble is on the guaranteed returns of the consulting agreement – opportunity cost. If she believes that the consulting contract is of higher value, she will choose to invest in specific knowledge.

While the tenured academic has a basis for job security in the university, by choosing to accept consulting with a firm, she is investing in knowledge which is largely only useful within that firm. General human capital (university research) can be transferred across multiple firms (for instance via TTO’s) or across universities (academic mobility and collaboration). Thus, once a faculty member invests in firm specific human capital there is a loss of efficiency in ‘changing horses’. This increased transaction cost from switching from firm specific to general human capital will result in a higher likelihood for consulting faculty to remain as consultants and thus will make it less likely for faculty to move from consulting to university work than otherwise.

Hypothesis 3 Academic consulting generates firm-specific human capital that creates a higher likelihood for a pattern of repetition than university research.
3 Methods

Our primary interest is on research that may have commercialisation potential in the relative ‘near term’. Patents are one measure of an invention with commercial viability. Growing portions of faculty are engaging in research that is patented (Azoulay et al., 2007). This may be due to a confluence of governmental policies and technology maturity particularly in the life sciences rather than any fundamental shift in the nature of university research. For example, scholars have found changes in both overall US policy strengthening intellectual property ownership and growth in biotechnology as a productive field of university research, influenced an increase in university patenting (Mowery et al., 2001). Patenting as a measure of industry collaboration is a relatively new development. University licensing and disclosure through the university TTO has been a much more common area of empirical research (Agrawal, 2006; Lach and Schankerman, 2004; Sine et al., 2003; Thursby et al., 2001).

To test these ideas, we have a multi-stage research design. We constructed a relevant sample of serial inventors who are active faculty members at US research universities. Next, we ran extensive descriptive analysis on the sample. Then we created transition probability matrices to access the stability of sequential decisions and relate this to human capital. Finally, we use several econometric models with a number of inventor, university and patent characteristics relevant to the patent assignment pattern of these academic inventors.

3.1 Sample frame

First, we constructed the entire patenting history for 349 US faculty members. These academic scientists and engineers have generated 8,079 patents and work in 73 different universities. This sample is a subset of those originally identified in prior research through an extensive matching process between faculty members from the US national research council and patent inventors in the NBER patent database (Hall et al., 2001; National Research Council, 1995; Thursby et al., 2009). For the study all faculty members were conditioned on having at least one patent assigned solely for profit firm and also at least one patent solely or jointly assigned to a university.

Searching patent records by faculty name, and location we were able to identify the universe of patents for each faculty member. The data collection begins with the first patent found for each faculty member and goes through the end of 2006. Due to the original structure of the data, the faculty members in our sample work at the same university throughout the 1990’s. A few have moved since the year 2000 and we incorporate additional patents in this work when we identify the inventor is still a faculty member. In this analysis, the institute of record however remains the university employer from the 1990 decade. If an inventor left his academic appointment and either retired or took fulltime industry or government work, the patent collection ends with the last application date covering his academic employment. A few of our inventors have taken a leave of absence from their academic department. As long as they are still listed in the department, we continue to code them as faculty members and collect data on them while on leave and after their return to academia.
3.2 Descriptive statistics

Our data cover a small number of patent applications starting in 1966 and through the 1970s. Following the overall rise in academic patenting a sharp increase in annual patents among our serial inventor faculty members occurs in the middle of the 1980s continuing through the 1990s. Figure 1 shows the annual patent applications by three major fields of study life science, engineering and physical science (National Research Council, 1995). The serial inventors have a mean of 23 patents each. Seven inventors have more than 100 patents while 24 have four or fewer patents.

Figure 1 yearly patent application by field (see online version for colours)

Figure 2 shows a scatter plot of the inventors’ total number of patents versus the percentage of those patents assigned to a firm. The average percentage of patents assigned directly to firms is 47.6%. This is higher than the 25% reported in the general science and engineering faculty assignments. However, it is reasonable considering we conditioned the sample on faculty who we identified as assigning at least one patent to a firm (Audretsch et al., 2006; Thursby and Thursby, 2005). Thus for the subset of faculty with some level of patent assignment to a firm, about 1/2 of their patents are owned by firms over their patenting careers. Note the spread of our inventors seems relatively uniform across the spectrum of percent firm assignments.

Figure 2 Percent firm assigned by inventor (see online version for colours)
We further explore whether a life cycle effect would be similar among faculty members of different vintage cohorts (Levin et al., 1991). For example, would the consulting trajectory for faculty starting their academic careers in the 1960’s be different from those in the 1980’s. Clearly, some shifting in overall activity is expected given the rise in university patents starting in the 1980s. What has not been studied is how this overall increase in academic patenting may affect the ownership patterns of patents with faculty inventors.

Based on a panel of over 3,800 academic life scientists Azoulay et al. (2007) find evidence of a shift in the timing of patenting activity. They created three cohorts from their faculty sample (covering 1967 to 1990) and plotted the hazard of a first patent for each cohort within the first 10 years of their careers. They found a higher propensity of patents for the younger cohort (granted PhDs from 1986 to 1990) than the older cohort (granted PhDs in 1967–1975). They posit that one reason for this change may be the increased legitimacy of patenting as a reputable form of scientific output in the life sciences. Expanding this investigation beyond life sciences is one goal of our work here.

Figure 3  PhD year panel per cohort (see online version for colours)
We explore the difference in time across our inventors by establishing cohorts by year of attainment of a terminal degree (PhD or MD). Following Azoulay et al. (2007), we created six balanced and non-overlapping cohorts three of which are presented in Figure 3 plotted by time from PhD to each patent. The four middle cohorts each cover five years. The beginning one covers from PhD year 1940 to 1964 to include ten inventors with PhD’s prior to 1954. This is the largest cohort with 68 inventors. In addition, the last cohort covers from 1985 to 1993. The smallest cohort is from 1965 to 1969 with 46 inventors. Each remaining cohort has between 52 and 59 inventors. The data shows that more recent faculty members are patenting earlier.

We also included a vertical line denoting estimated tenure at seven years from attainment of PhD. We discover that the earliest cohorts covering PhD years from 1940 to 1969 have almost no patent applications prior to tenure. The most recent cohort however has a large number of applications before the seven-year mark. In both the recent cohorts although there is patenting activity prior to tenure, there is also a sharp tick upward in the first few years after tenure would be expected (years 8 through 13). While some of this effect is explained by the overall rise in patenting relative to career stages of our inventors, it is the case that we have 14 faculty members earning PhD’s from 1963 to 1969 with pre-tenure patents. Further the rate of patenting growth in early patenting for those earning PhD’s from 1985 to 1993 versus1980 to 1984 is striking.

3.3 Transition probabilities: life cycle human capital

The TTGM life cycle model specifies that the profit function maximised represents the cumulative career results of a faculty inventor. Correspondingly, the human capital model argues that there are switching costs of moving away from a stream involved with ‘specific’ knowledge. This view argues that there is going to be a bias to pursuing follow-on projects with the same sponsor of specific knowledge as opposed to either pursuing a subsequent project of ‘general’ knowledge or a subsequent project of specific knowledge with a different sponsor.

Through this lens, we investigate the pattern of assignments for a given faculty member over time. In particular, we explore the ‘Transition Probability’ of retaining the same assignment type (university or firm) from one patent to the next versus a ‘switch’ to the opposite assignment type (Scherer and Glagola, 1994; Zeng and Cook, 2007). Since multiple patents may be produced by a single ‘research stream,’ a focal patent may actually be tied to a prior or subsequent patent – which could drive ‘stickiness’ of assignment type in either direction.

To gain insight, we turn to the literature of ‘sequential decision analysis’ for additional understanding of the interactions of these corresponding and competing theories (life cycle, university context and human capital). Whether solved mathematically or via simulation, a common formulation for this type of problem is called ‘state-based modelling’. In its most general sense a ‘state’ is a description of the relevant details of the process at a given point in time (Chao and Manne, 1983). As a simple example, a classic stochastic process is the ‘gambler’s ruin’ problem. At its most basic level, the ‘state’ in a gambler’s ruin is the value of the money held by the player at that point in time. The decision made is the bet to be placed on the next play of the game. Assume that at time \( t \), the state of the player’s bankroll is \( C_t \) (for ‘Chips’). If the player bets an amount \( B_t \), then at the end of the next play the value of \( C_{t+1} = C_t + B_t \) if the player wins the hand and \( C_{t+1} = C_t - B_t \) otherwise (Ross, 1996).
The state definition can be a multi-attribute trajectory with as many elements as necessary to adequately describe the current condition of the entity for which a decision must be taken. Other components of a state based model include: the list (and descriptions) of ‘resulting states’ (the state at time \( t + 1 \)) that might be obtained given the presence in a specific state at time \( t \); a description of a set of actions that can be taken – with the expected cost of each action; the conditional probability of going from a given state to a new specified state in the epoch from time \( t \) to time \( t + 1 \) based on the action taken and the resulting rewarding for that change in state (Littman, 1996).

We begin by defining our state as the assignment of a given patent (\( U – \) university or \( F – \) firm) and seek to gain understanding what factors influence the ‘transition probability’ of staying in the same state for the next patent in the series or in changing states.

To explore sequential decisions relative to the impacts of life cycle and ‘specific knowledge’ switching costs, we constructed a set of ‘transition probability matrices (TPMs)’. Looking at the faculty member’s time-ordered series of patents, we calculated the conditional probability that the next patent in the sequence would be assigned to the university (\( U \)), a firm (\( F \)) or other (\( X \)) given that the current patent has a known assignment (\( X \) here could be a jointly assigned patent, unassigned or a patent assigned to the federal government). To illustrate TPMs we have created a ‘decision tree’ form to show a visual picture of the matrices. Figure 4 shows each patent in the repeating series at the same level of the diagram. The number of current/prior states included in calculating a transition probability is referred to as ‘orders’, ie, a TPM based solely on the current state is termed a ‘first order TPM’. While the use of the current state plus one prior state is called a ‘second order TPM.’ Looking at this diagram, if we start with the transition from university to firm assignments (UF), at the top left side of the diagram we see 21% probability of this single state change. For firm to university assignment changes we find 19% probability. A shift from specific (firm) knowledge to general (university) knowledge is less likely than the other direction. This result is in keeping with the human capital framework that specific knowledge has greater switching costs than general knowledge.

**Figure 4** 1st and 2nd order transition probabilities (see online version for colours)

Notes: UF (21 %) > FU (19%); UF (16%) > FFU (12%)

Next we drill deeper and find the TPMs for the 2nd order transitions. In the 2nd level of the diagram following the UUF tree we find 16% probability while on the right hand side we find FFU at 12%. These are statistically different and show that it is less likely that faculty return to university patents after two prior firm assigned patents. Again we find
support for the pattern repetition of specific knowledge. We also uncover a path dependency in the data by looking at these state changes. While this is detrimental to the use of some analysis tools such as a Markov decision process, it does offer some suggestions for treatment of variables in a regression format that may be useful. We will pick up this idea again in the econometric section below.

4 Econometric models

We use logistic models to study the probability of patent assignment to a university or a firm. Since we are unable to observe the actual research and consulting decisions made by faculty members, we rely on the patented outcome of such decisions for clues as to what factors influence these decisions. We include variables on the individual, the university and the patent itself for impact on the patent assignment pattern during an academic career.

If firm assigned patents have a higher probability of occurring later in an academic career, this provides support for the hypothesis from the life cycle model that faculty industry engagement is delayed relative to university research. In the model we incorporate lagged variables to search for inferences on specific knowledge inertia in academic careers.

4.1 Independent variables

The model contains a number of individual characteristics for the faculty inventors. We include the age of the faculty inventor at the time of the patent application (AGE). If the age variables yield a higher propensity for firm assigned patents for later staged careers, it supports the hypothesis that consulting occurs after establishment of university research. We construct the age variable by adding 28 years to the date of PhD awarded. For example, if a faculty member earned a PhD in 1980 and had a patent application in 1990, the age of 38 is entered for this observation.

We established a dummy variable to help control for the increase in US university patents since the passage of the ‘Bayh-Dole’ act in 1980. Patent Post BD is coded 0 for any patent application date prior to 1981 and coded 1 thereafter. We also include controls for the previously mentioned PhD cohorts. Thus five of the six cohorts are included in the estimation models. For example, PHDCohort_1969 is coded a ‘1’ if the inventor received his PhD between 1965 and 1969, zero otherwise. The first cohort ending in 1964 is the omitted category. We were unable to identify the PhD year for 15 of our inventors and they are not included in the econometric analysis.

We add controls for the major program area of each faculty member. For field of study, we use the major program area provided by the National Research Council (NRC) (1995). The fields are life sciences, physical sciences and engineering. We include Life Science Faculty = 1 if the department is in the life sciences. Likewise Engineering Faculty = 1 if the inventor resides in an engineering department (physical science is the omitted field). Prior research found that life science faculty show a higher probability to assign to the university than physical scientists (Thursby et al., 2009). We therefore expect Life Science Faculty to trend towards university assignment if it is significantly different from the omitted group.
We incorporate two reputational variables. First is a department level quality measure on a 0 to 5 scale from the national research council (National Research Council, 1995). Higher values of Dept Quality are indications of higher quality departments as measured by the 1993 survey responses gathered by the NRC (1995). In a few cases faculty are listed in multiple departments. In such instances, we took the primary department or if this could not be determined, we took the department with the highest NRC rating. Caution must be taken to interpret this variable because the presence of our faculty inventors is an endogenous component of the rating itself.

Second, we added a dummy variable for the faculty members included in the ISI highly cited listings. This list, based on citations to published articles, represents no more than a maximum the top 250 scholars across 21 different academic fields. Zucker et al. (2002, 1998) have found a vital role of star scientists on commercialising biotechnology discoveries. This Thompson ISI® database is utilised as an alternative to expand the study of star scientists beyond the biotechnology industry. In a study on migration of star scientists, Zucker and Darby (2007) use ISIHighlyCited.com to proxy for stars across six different technology fields. Research on consulting provides some evidence that higher quality faculty (those with more publications) tend to consult less (Jensen et al., 2010). Though the ISI measure is on publication citations, we would still expect those faculties with a higher level of citations to consult less and therefore assign more patents to the university.

Next we include institutional characteristics in the model. We start with a dummy variable coded 1 if the university employer is a public university (public university). Public universities often incorporate an economic development aspect in their mission. This may encourage faculty to work more closely with local industry. Prior work found faculty from public universities will have a higher probability of assignment to firms than faculty at private universities (Thursby et al., 2009). We expect a similar result over the career of our faculty inventors.

Additionally, we explore the commercialisation assistance provided in the university context. We include four variables related to university commercialisation aids. First we include incentives for faculty disclosure to the university. This is entered as a variable for the percentage of royalty sharing faculty inventors receive from the university TTO. For these universities this varies from 20% to 67% with an average of 36% (univ share royalties). Prior work shows a correlation between the share of royalties and share of patents assigned to the university (Lach and Schankerman, 2004; Thursby et al., 2009). It is possible that faculty in higher share universities do not spend time augmenting their income by consulting (Jensen et al., 2010). Both these considerations yield an expectation towards universities for higher inventor share of royalties.

Next, we look for specific commercialisation effect of the university TTO. We include dummy variables for the presence a TTO, entered as time varying. For example, the TTO at the University of Arizona was established in 1988. The Arizona academic inventors in our sample have 20 patents with application dates prior to 1988 and 133 after this time. The 20 are coded ‘0’ and the balance is coded as ‘1’.

TTOs are created by universities to help appropriate the rents from faculty discoveries. TTO officers provide assistance to faculty and firms in generating formal licensing contracts for university technology (Link et al., 2007). We therefore expect (presence of univ TTO) to tend towards increasing the probability of assignment to a university.
Two control variables are included to help isolate the proposed impact of TTO presence and policy. The presence of a university business incubator is included as a major investment by the university to develop university related technologies (Phan et al., 2005). Business incubators in many universities help get faculty research beyond the prototype stage and into industrial development. The predicted direction for this control variable, (univ bus incubator) is not clear. On the one hand, the incubator assists faculty and industry startup firms under the guidance of the university. This would tend to increase the technology licensed from the university (and therefore increase the assignment of patents to the university). However once the startup firms are launched, faculty involvement can continue in startup laboratories to further develop the technology. This activity would result in new patents generated and likely assigned to the firm rather than the university.

Our second university commercialisation control variable is based on the presence of a university related science park. University science parks are located near research universities to bring both large and small firms into more accessible contact with university researchers (Link et al., 2007). Science parks tend to be real estate driven. They are often organised through 3rd party developers with the cooperation of the university (Link and Scott, 2006; Phan et al., 2005). Science parks are by their nature, more loosely tied to university administration than either TTOs or campus incubators (Link et al., 2006; Link et al., 2007). The third party arrangements typical between science parks and universities may provide increased opportunities for direct faculty consulting. Thus, we expect Univ Science Park to increase the likelihood of firm assignment.

The last set of variables we incorporate are the patents characteristics themselves. By examining citation patterns and claims, we look for significant impacts on the type of patent and the ownership of the intellectual property. The patent applications cover from 1966 through July of 2006. We include citations to prior US patents sometimes called ‘backward citations’ from the focal patent (citations to prior art). Patents with reference to a large number of previous patents are considered to be contributing to a deep base of prior invention. Patents with relatively more citations to prior patents are more incremental than otherwise. We expect consulting to yield more incremental patents than university research and therefore consistent with earlier results, this variable should trend towards the higher the number citations to prior art, the more likely the assignment to a firm (Thursby et al., 2009).

We also have the number of claims in the patent document itself (claims). We expect the higher importance of the patent the larger the number of claims. However, it is possible the structure of the claims is also an indicator of the patent attorney rather than the value of the underlying discovery. We expect more foundational patents to be assigned to the university and typically these ‘enabling’ patents would have more claims than more incremental efforts. Therefore we look for this variable to trend towards university assignment the higher the number of claims.

The number of citations on subsequent patents, sometimes called ‘forward citations’ is collected as of October of 2007 (forward pat citations). This variable is susceptible to truncation errors. Patents more recently issued do not have the same amount of time to collect forward citations as do older ones. Additionally it has been shown that university lags in citations are longer than firm citation lags (Sampat et al., 2003). Therefore robustness checks are done to reduce truncation errors in the newer patents.
Our major interest is on patents assigned to a university versus those solely assigned to a firm. For this reason we drop patents which are jointly assigned to differing assignment types (such as both a university and a firm). We also drop a small number of patents assigned to the federal government for our econometric analysis. Summary statistics for the remaining 7,346 patents with the key inventor, university and patent characteristics are presented in Table 1.

### Table 1 Summary statistics

<table>
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<th>Variable name</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. dev.</th>
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<td><strong>Individual characteristics</strong></td>
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<tr>
<td>Assignment type (1 = firm)</td>
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<td>0.52</td>
<td>0.49</td>
<td>0</td>
<td>1</td>
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<tr>
<td>Age (time of pat appl)</td>
<td>7,061</td>
<td>50.77</td>
<td>11.7</td>
<td>21</td>
<td>91</td>
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<tr>
<td>Life science faculty</td>
<td>7,346</td>
<td>0.18</td>
<td>0.38</td>
<td>0</td>
<td>1</td>
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<tr>
<td>Patent post Bayh-Dole (1981)</td>
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<td>0.95</td>
<td>0.21</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Engineering faculty</td>
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<td>0.53</td>
<td>0.49</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Dept quality (NRC)</td>
<td>7,346</td>
<td>3.74</td>
<td>1.10</td>
<td>0</td>
<td>4.97</td>
</tr>
<tr>
<td>ISI highly cited scholar</td>
<td>7,346</td>
<td>0.13</td>
<td>0.33</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Lagged assignment ((T-2, T-1))</td>
<td>6,703</td>
<td>0.38</td>
<td>0.48</td>
<td>0</td>
<td>1</td>
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<tr>
<td><strong>University characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Public university</td>
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<td>0.55</td>
<td>0.49</td>
<td>0</td>
<td>1</td>
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<tr>
<td>Univ share of royalties</td>
<td>7,346</td>
<td>36.29</td>
<td>8.64</td>
<td>20</td>
<td>67</td>
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<tr>
<td>Presence of univ TTO</td>
<td>7,346</td>
<td>0.9</td>
<td>0.29</td>
<td>0</td>
<td>1</td>
</tr>
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<td>Univ bus incubator</td>
<td>7,346</td>
<td>0.29</td>
<td>0.45</td>
<td>0</td>
<td>1</td>
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<td>Univ science park</td>
<td>7,346</td>
<td>0.65</td>
<td>0.47</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>Patent characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Citations to prior art</td>
<td>7,346</td>
<td>15.75</td>
<td>28.35</td>
<td>0</td>
<td>370</td>
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<td>Claims</td>
<td>7,346</td>
<td>21.69</td>
<td>19.81</td>
<td>0</td>
<td>513</td>
</tr>
<tr>
<td>Forward pat citations</td>
<td>7,346</td>
<td>15.13</td>
<td>31.18</td>
<td>0</td>
<td>778</td>
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</table>

#### 4.2 Bivariate logit models

Our econometric results are based on a series of binomial logistic regressions with patent assignment as the dependent variable \((1 = \text{firm assignment})\). Table 2 shows results from the estimation. The odds ratios presented identify the likelihood a factor is more likely to correlate with patents assigned to a firm if it is above 1.0. An odds ratio is the probability of an event divided by one minus the event probability (Cohen et al., 2003). For example, in the model, each additional year of age after PhD attainment increases the likelihood that the patent will be assigned to a firm rather than the university by 2.7%.

The data consists of multiple patents over the career of our inventors. Thus, we need to account for a serial dependence in the residuals of our estimates. We have used clustered robust standard errors in the model presented (Cohen et al., 2003). The standard errors are clustered by inventor. This increases the standard error terms and reduces the significance level of a number of our covariates (relative to robust standard errors without clustering). For example in our original models both TTOs and university business
incubators were statistically significant (at a 1% level) and trending to increase patent assignments toward the university. With standard errors clustered by inventor, neither entity remains significant. We retain TTOs, incubators and science parks in the models however as we are interested in their differential contributions (or lack thereof) to the consulting patterns of university faculty.

**Table 2**

<table>
<thead>
<tr>
<th>Bivariate model: university assigned (0)</th>
<th>Model odds ratio</th>
<th>Robust std error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>1.027*</td>
<td>0.015</td>
</tr>
<tr>
<td>Patent post bd (1981)</td>
<td>1.119</td>
<td>0.959</td>
</tr>
<tr>
<td>Life science faculty</td>
<td>0.939</td>
<td>0.164</td>
</tr>
<tr>
<td>Engineering faculty</td>
<td>0.978</td>
<td>0.129</td>
</tr>
<tr>
<td>Dept quality (NRC)</td>
<td>0.946</td>
<td>0.047</td>
</tr>
<tr>
<td>ISI highly sited scholar</td>
<td>0.61***</td>
<td>0.105</td>
</tr>
<tr>
<td>PhDCohort_end_1969</td>
<td>1.74**</td>
<td>0.445</td>
</tr>
<tr>
<td>PhDCohort_end_1974</td>
<td>1.463</td>
<td>0.416</td>
</tr>
<tr>
<td>PhDCohort_end_1979</td>
<td>1.309</td>
<td>0.433</td>
</tr>
<tr>
<td>PhDCohort_end_1984</td>
<td>1.657</td>
<td>0.685</td>
</tr>
<tr>
<td>PhDCohort_end_1993</td>
<td>2.212</td>
<td>1.095</td>
</tr>
<tr>
<td>Univ(T-2), firm(T-1) asn</td>
<td>5.151***</td>
<td>0.617</td>
</tr>
<tr>
<td>Firm(T-2), firm(T-1) asn</td>
<td>26.667***</td>
<td>4.101</td>
</tr>
<tr>
<td>Firm(T-2), univ(T-1) asn</td>
<td>3.133***</td>
<td>0.415</td>
</tr>
<tr>
<td>Public university</td>
<td>1.284**</td>
<td>0.161</td>
</tr>
<tr>
<td>Univ share of TTO royalties</td>
<td>0.981***</td>
<td>0.007</td>
</tr>
<tr>
<td>Presence of univ TTO</td>
<td>0.777</td>
<td>0.158</td>
</tr>
<tr>
<td>Univ bus incubator</td>
<td>0.858</td>
<td>0.103</td>
</tr>
<tr>
<td>Univ science park</td>
<td>1.032</td>
<td>0.128</td>
</tr>
<tr>
<td>Citations to prior art</td>
<td>1.02***</td>
<td>0.004</td>
</tr>
<tr>
<td>Claims</td>
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<td>0.002</td>
</tr>
<tr>
<td>Forward pat citations</td>
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<td>0.002</td>
</tr>
<tr>
<td>Clustered errors</td>
<td>Yes</td>
<td></td>
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<tr>
<td>Year fixed effects</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Number obs =</td>
<td>5715</td>
<td></td>
</tr>
<tr>
<td>Pseudo R2</td>
<td>0.3414</td>
<td></td>
</tr>
</tbody>
</table>

Notes: *** %; **5%; *10% significance level

A key element of the estimation is the incorporation of the information from our TPMs into the model. The motivation for evaluating transition states was the pattern of repetition theorised by firm specific human capital in our third hypothesis. Recall in the TPMs we found a path dependent pattern where the prior two states seemed to give strong predictors of the next state. Using this information, we adapted a rolling dummy variable using lagged patent assignments to characterise the entire patent chain. For
example if a focal patent is the 10th in the patent chain and the 8th patent is assigned to a university and the 9th patent is assigned to a firm, the patent will be coded ‘1’ in the ‘UNIV(T-2), FIRM(T-1)_ASN’ dummy variable. If this 10th patent is assigned to a firm, the 11th patent will be coded as a ‘1’ in the ‘FIRM(T-2), FIRM(T-1) ASN’ variable and zero in the other categories.

The use of lagged variables on the right hand side of the model necessitates removal of the 1st two patents for each inventor to establish the assignment category of the third patent. This reduces our sample size by 640 patents. We also focus on the firm and university assignments so we delete patents preceded by an ‘other’ assignment (for example government or unassigned). This condition reduces our sample by a further 746 patents.

The model yields three especially telling results related to the assignment ‘state’. First, all three lagged variables are significant at the 1% level and each is strongly increasing the likelihood of firm assignment (relative to the ‘UNIV(T-2), UNIV(T-1)’ omitted category). Second, the effect size on the ‘UNIV, FIRM’ variable and the ‘FIRM, UNIV’ variable lend additional support to the notion of specific knowledge ‘stickiness’. The odds ratio for UF is 5.151 while the odds ratio for FU is 3.133 (they are significantly different at a 1% level). Both have one university patent and one firm patent in the prior pair of patents. While both increase the likelihood of firm assignment, note the measure with the most recent FIRM assignment has a larger effect size. Thus, if the last patent was assigned to a firm, the next one is more likely to also go to a firm. This result is consistent with our theory of the increased switching costs for specific knowledge embodied in consulting knowledge and supports our third hypothesis that firm specific human capital will more likely result in a pattern of repetition.

Third, the addition the lagged variables more than triples the amount of variance explained over the models without such state factors. Our model has a pseudo Rsquare of 0.34 while the same model without the lagged variables achieves a pseudo Rsquare of 0.089. This indicates not only strong support for the value of knowledge on the prior patent sequence but it also provides indication that the transition information is more helpful in explaining consulting activity than the life cycle or university context for our serial inventors.

In the model, the AGE variable is significant (10% level) and provides support for the increase in firm assigned patents as the age of the inventor increases. This result supports our first hypothesis that consulting will have a tendency to develop later in a career than university research.

ISI highly cited is highly significant (1% level) and correlates with patents assigned to the university. This provides evidence that ‘star scientists’ are not overall inclined towards industry consulting. Indeed this effect is one of the strongest in both significance and effect size across a variety of models we tested. This may be taken as a sign of preference for university research over consulting. The ‘star’ scientist should have enough market power to overcome typical principal agent problems (Fuller and Rothaermel, 2012). In short, they should be able to work on the projects of their choosing and it seems clear they are not choosing consulting.

Public university serial patenters are significantly (5%) more likely to assign to a firm. This provides support for a differential effect from the land grant mission of many public universities to help local economic development compared with private universities.
University policies also seem to have an impact on the likelihood of patent assignment. The higher the percentage of university share of royalties with the inventor, the more likely the patent will be assigned to the university. This matches earlier research and supports the idea that university licensing policies can have an impact on faculty choices for their types of industry engagement (Lach et al., 2004; Thursby et al., 2009). This result supports Hypothesis 2a which higher share of royalty income would increase university assignment and reduce relative industrial consulting.

The presence of university TTO is not a significant factor in the model. We thus do not have support for Hypothesis 2b that the presence of a TTO would increase university assignment relative to industrial consulting. In sensitivity checks, we found a significant effect in the predicted direction for estimation models without the lagged variables. It seems the large impact of the specific capital pattern overcomes the TTO factor in the full model.

The final set of characteristics is related to the patents themselves. Citations to prior art is highly significant (1% level). Increasing the number of citations by one in the focal patent will increase the likelihood of firm assignment by 2%. Patents with more citations to prior art are considered to be more incremental as they are building upon numerous other patents rather than groundbreaking scientific papers. This supports findings in prior work which demonstrate that firm assigned patents are more likely to be incremental than those assigned to a university (Thursby et al., 2009).

### 4.3 Robustness checks

We explored some additional robustness checks in the analysis beyond those previously mentioned. Forward citations are not significant in an unreported model incorporating the NBER constructed variable original (Trajtenberg et al., 1997). This necessarily reduces the sample size to those patents granted between 1975 and 1999. This is the most appropriate model for a forward citation measure as patents granted in 1999 have eight years to accrue citations thus reducing the previously noted censoring problem with this measure.

To check for outliers in our data we created a ‘star inventor’ variable from our dataset. We calculated three standard deviations above the mean for a lower limit of the number of patents a ‘star inventor’ would need (Rothaermel and Hess, 2007). This process yielded seven ‘stars’ each with more than 100 patents. We ran model 4 after deleting the 912 patents these inventors created. The results are quite similar to prior results except public university is no longer significant.

We also originally included faculty member election to the national academies in either science or engineering [elected National Academy of Sciences (NAS) or NAE]. New academy candidates are nominated by current members and then are voted on by the entire membership. The NAS currently limits new inductees to 72 per year. There are approximately 2,000 active members of NAS (Alberts and Fulton, 2005). Some scholars have suggested patenting is now more readily accepted among faculty members, however there is little evidence to suggest this is true for consulting (Azoulay et al., 2007; Ding et al., 2007). In our final models this variable was deleted as it was not statistically significant with the clustered standard errors. It did mirror in direction the ISI highly cited variable with strong tendency for assignments to the university.
5 Discussion/conclusions

5.1 Life cycle

Our descriptive data show that more recent PhD graduates have a different patenting profile than graduates in the older cohorts. We considered the patenting profile of six different cohorts and found that faculty member are patenting earlier in their careers than did their predecessors. This result supports and extends the prior work of Azoulay et al. (2007) in their study faculty in the life sciences.

Our logistic regression demonstrated support for patenting later in the career when controlling for a variety of individual, university, patent and transition characteristics. This key age indicator lends further support to the role of industry engagement occurring later in the career trajectory of these academic scientists than more traditional university assigned patents. We thus found support for the first hypothesis that consulting occurs later than university research in the inventive career of academic researchers.

5.2 University context

Econometric analysis also provides several insights into university settings and their likely impact on faculty research driving patenting activity. Increasing the percentage of licensing royalty sharing favours university assignment. This confirms Hypothesis 2a that higher revenue sharing will increase university owned research. We extend the prior finding that universities with higher license revenue sharing do tend to have a higher likelihood of university research. Thus from a policy perspective, university administrators who want to increase their portion of university assigned research may want to focus on sharing licensing revenues and other methods of increasing the opportunity costs for faculty to engage in industrial consulting. However, the TTOs, business incubators and university science parks are not significant in our full model. Therefore, we are not able to support Hypothesis 2b that these elements of the university environment are substantively helpful in increasing university research over consulting.

Further research in overall faculty productivity in patents and publications may yield some new insights into commercialisation aids supported by the university. Given the benefits of industry consulting for faculty and graduate students, a more fruitful approach to policy changes might be to increase the overall output rather than increase university research at the expense of knowledge generating consulting and entrepreneurship.

The ISI highly cited variable was significantly correlated with increasing university assignment odds across all our estimations. This is somewhat counter to the role of ‘star scientists’ as entrepreneurial catalysts though perhaps it supports the idea that stars are less interested in industrial consulting themselves. It would be intriguing to look at graduate students from the ‘star’ labs to see if they are more inclined towards industry engagement. It does however suggest that ‘good’ faculty are not assigning to firms at the rate of our other faculty inventors. Some have argued that renowned academics have more influence than typical agents and may well be taking patents out the ‘back door’ as the university is loath to stop them (Markman et al., 2007). We find quite limited evidence to support this viewpoint in our results.
5.3 General versus specific human capital

Building on the idea of firm specific human capital we are able to find support for our third and final hypothesis that specific human capital is more likely to generate a pattern of repetition. Academic consulting for industry generates firm specific human capital. Human capital theory says that once a commitment to specific knowledge is made, there are increased opportunity costs to move away from that investment. Our empirical results demonstrate that once a professor starts consulting with a firm, he is more likely to continue consulting. We find this result both in the analysis of transition probability matrices and logit regression modelling. A faculty member is less likely to move from consulting to university inventions than the other direction.

We tested this idea with the use of transition probability matrices which lead us to create a set of lagged variables which more than tripled the explanatory power of the econometric models over models with only life cycle and university characteristics. The impact of such transitional variables raises the question for future research of better ‘state’ definitions. In other words, the prior pattern of assignment seems to be a major influence on the next assignment type. Finding this ‘augmented state’ is an avenue for future work that is beyond the scope of this paper.

5.4 Conclusion

Together these empirical tools help us learn more about consulting and university research by faculty inventors. We submit this is not only useful to examine from a policy perspective but also more generally, to study a complete picture of faculty contributions to industrial innovations. As we have argued, the pattern of this intellectual property assignment provides insights on consulting and entrepreneurial activities beyond those captured in traditional metrics gathered from TTOs or those prior works based on patents assigned to universities.

We set out to identify significant variables in the observed patent assignment patterns of academic serial inventors. We theorised that industry engagement would have an effect on the life cycle patterns for these inventors and commercialisation policies at the university level would play a role in assignment of patents. We also predicted consulting related knowledge would be ‘stickier’ than university knowledge due to the firm specific nature of consulting. Each of these aspects has proven to be informative.

We also hoped to be able to shed more light on the debate over ‘back door’ versus ‘legitimate assignment’ debate on academic patenting. A number of possible explanations have been advanced for the differences between university and firm assigned patents. Some assert that firm assigned patents by active faculty members are by nature nefarious (Audretsch et al., 2006; Link et al., 2007; Markman et al., 2007). We however reinforce prior findings that firm assigned patents are incremental in nature. This result is quite robust to a variety of model specifications. Therefore, the ‘best’ patents do not seem to be going out the back door.

The major contributions of this research are the following. We have used existing life cycle models to test the idea that consulting occurs later in the career span of academic scientists. We find that indeed our proxy for consulting (firm assignment of patents) is more likely the later the patent application is in the career cycle for our inventors. Second, we found strong evidence that faculty performing industry consulting is more likely to continue consulting in subsequent work. We have explored an underutilised set
of tools on sequential decisions that have potential to provide additional insights to the field of strategic management. Our use of rolling lag variables based on this transition probability increased our variance explained in the regression model by a factor of three. Finally, we have further extended findings on university revenue sharing and cohort efforts on academic consulting.

References
A career in innovation: serial faculty inventors


Thursby, J.G. and Thursby, M.C. (2005) ‘Faculty patent activity and assignment patterns’, REER 2005, Georgia Institute of Technology, Emory University, Atlanta, GA.


**Notes**

1. This is in addition to including year fixed effects in our models.
2. Professor Al Link generously shared university science park data. The TTO, incubator and additional science park data was collected from AUTM, university websites and press releases.
3. In robustness checks, we ran the model including these 746 patents and the results are largely consistent with what we report in Table 2. The TTO variable however becomes significant and the age variable drops out of significance in the larger sample. All coefficients are consistent and we report the smaller properly selected sample for the model in the paper.