NBER WORKING PAPER SERIES

UNIVERSITY PATENTING:
ESTIMATING THE DIMINISHING BREADTH OF KNOWLEDGE DIFFUSION AND CONSUMPTION

Carlos Rosell
Ajay Agrawal

Working Paper 12640
http://www.nber.org/papers/w12640

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2006

We are grateful to Azim Essaji, Maryann Feldman, Avi Goldfarb, Brent Goldfarb, Aamir Hashmi, Ignatius Horstman, Rhys Mendes, Diego Puga, Frank Rothaermel, Bhaven Sampat, Mark Schankerman, Tim Simcoe, Nadia Soboleva, Marie Thursby, Daniel Trefler, Rosemarie Ziedonis, and participants at the 2005 Canadian Economic Association meeting, 2005 Roundtable for Engineering Entrepreneurship Research conference (Georgia Tech), and 2006 ExTra workshop (EPFL) for helpful comments. Errors and omissions are our own. This research was partially funded by the Social Sciences and Humanities Research Council of Canada (Grant No. 410-2004-1770). Their support is gratefully acknowledged. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

University Patenting: Estimating the Diminishing Breadth of Knowledge Diffusion and Consumption
Carlos Rosell and Ajay Agrawal
NBER Working Paper No. 12640
October 2006
JEL No. I23,O33,O34

ABSTRACT

The rate of university patenting increased dramatically during the 1980s. To what extent did the knowledge flow patterns associated with public sector inventions change as university administrators and faculty seemingly became more commercially oriented? Using a Herfindahl-type measure of patent assignee concentration and employing a difference-in-differences estimation to compare university to firm patents across two time periods, we find that the university diffusion premium (the degree to which knowledge flows from patented university inventions are more widely distributed across assignees than those of firms) declined by over half during the 1980s. In addition, we find that the university diversity premium (the degree to which knowledge inflows used to develop patented university inventions are drawn from a less concentrated set of prior art holders than those used by firms) also declined by over half. Moreover, in both cases the estimated increase in knowledge flow concentration is largely driven by universities experienced in patenting, suggesting these phenomena are not likely to dissipate with experience.

Carlos Rosell
Department of Economics
University of Toronto
140 St. George Street, Suite 707
Toronto, ON, M5S 3G6 CANADA
carlos.rosell@utoronto.ca

Ajay Agrawal
Rotman School of Management
University of Toronto
105 St. George Street
Toronto, Ontario M5S 3E6
CANADA
and NBER
ajay.agrawal@rotman.utoronto.ca

1 Introduction

Amongst the most striking developments on American university campuses over the past quarter century has been the rapid rise of patenting to lay claim to and protect intellectual property associated with novel and practical inventions developed by university researchers. Indeed, in just 13 years, from 1980 to 1993, the number of patents issued annually to US universities increased by 315%, from 390 to 1620.[1] This dramatic shift in academic behavior has been attributed to many factors. Principal among these are developments in the fields of microbiology and computer science, an expansion in the range of patentable matter (e.g., genetically modified life forms, software), the creation of the Court of Appeals for the Federal Circuit, and, most commonly, the passage of the Bayh-Dole Act (1980), which granted universities extensive rights to patent and retain ownership of innovations produced with federal government funding.

Although many observers have characterized the dramatic rise of university patenting as a windfall for the American economy - indeed, *The Economist* went as far as describing the Bayh-Dole Act in particular as "possibly the most inspired piece of legislation to be enacted in America over the past half century" and citing university-based innovation as a key factor that facilitated America's industrial renaissance in the 1980s[2] - others have expressed a variety of concerns, most of which can be grouped into one of three categories: 1) a shift in focus from "basic" to "applied" university research,[3] 2) a decline in quality of university inventions, and 3) a decline in the dissemination of knowledge associated with university inventions.

Surprisingly, given the increasing level of concern over university patenting expressed in both policy circles and the popular press,[4] the evidence to date offers little support for the

[1] By comparison, the number of patents issued to other US non-government organizations increased by only 48% over the same time period.

[2] "Innovation's Golden Goose," *The Economist*, December 14, 2002, Vol.365 (8303), p. 3.

[3] Notwithstanding Stokes' legitimate grievances with respect to the basic/applied taxonomy (Stokes (1997)), we reference it here since most of the discourse on this topic has characterized research this way.

[4] "Patent on Human Stem Cell Puts U.S. Officials in Bind," *New York Times*, August 17, 2001, p. A1; "University Resolves Dispute On Stem Cell Patent License" *New York Times*, January 10, 2002, p. C11;

first two of these concerns. The first concern, that an increased focus on commercialization may induce university researchers to divert their energies away from basic research (Cohen et al. (1998); Henderson et al. (1998)), is predicated on the notion that it is more important for universities to provide basic than applied research. This is because the market is more likely to under-provide basic than applied research due to greater appropriability problems. Basic research is important though, since it often provides knowledge for subsequent applied research and product development, which in turn is the basis for long run productivity and economic growth.

However, empirical studies that examine whether professors substitute patenting for publishing, a rough proxy for changes in research focus, do not provide evidence of such substitution. Agrawal and Henderson (2002) examine the publishing and patenting output of electrical engineering, computer science, and mechanical engineering faculty at a major research institution (MIT) and present evidence suggesting that these two activities are complements rather than substitutes. Furthermore, Markiewicz and DiMinin (2005) and Goldfarb et al. (2006) examine the complement-substitute question more directly with data from a much broader sample of university researchers and find similar results. Moreover, these findings are not specific to US universities; several studies that examine the patenting-publishing relationship at various European institutions yield similar conclusions (VanLooy et al. (2005) - K.U Leuven in Belgium; Buenstorf (2005) - Max Planck Institute in Germany; Carayol (2005) - University Louis Pasteur in France; Breschi et al. (2005) and Calerini and Franzoni (2004) - various institutions in Italy).

The second concern is predicated on the notion that an increased focus on commercialization may induce researchers to shift resources towards the disclosure and patenting of lower quality inventions (Henderson et al. (1998)).[5] However, evidence presented by Mowery et al. (2004) shows that although the quality of inventions did decline after 1980, this was

"Bayhing for blood or Doling out cash?" *The Economist*, December 24, 2005, p. 115; Lieberwitz (2005); "Lilly Loses Patent Case to Ariad," *New York Times*, May 5, 2006, p. C1.

[5]The quality of inventions is measured by "importance," reflected by a count of subsequent citations, and "generality," reflected by the dispersion of citations received from patents in different technology fields.

due to the entry of universities with little patenting experience; it was not due to a general decline in quality of inventions patented by all universities. The implication of this finding is that the estimated decline is likely to be only temporary, while inexperienced universities learn the patenting process and how to most effectively manage their intellectual property portfolio.

Thus, it is only the third concern, relating to how the anti-commons limits the flow of knowledge, that has found traction in empirical evidence. In a study employing a difference-in-differences identification based on patent-paper pairs, Murray and Stern (2005) report findings that although publications linked to patents are associated with a higher overall citation rate, after the patent is actually issued, the rate declines substantially (by 9-17%). The authors note that the decline is particularly salient for articles authored by researchers with public sector affiliations, such as university professors. They interpret their findings as evidence of an anti-commons effect that results from moving intellectual property from the public into the private domain.

Our paper further addresses the third concern: restricting the widespread flow of knowledge associated with university inventions. However, where Murray and Stern focus on the decline in the *level* of knowledge flows, we focus on the *narrowing* of knowledge flows to a smaller set of recipients. Specifically, we examine whether, over time and conditional on being patented, university inventions are more likely to be cited by a more concentrated set of subsequent patent owners. Such a finding could reflect the outcome of a change in the management objectives of university intellectual property from broad knowledge dissemination towards limiting access, perhaps to maximize private returns to licensors.

Using a Herfindahl-type measure of patent assignee concentration associated with forward citations as a dependent variable and employing a difference-in-differences estimation (taking the difference of the change in concentrations over time between university versus firm patents), we estimate that the university diffusion premium (the degree to which knowledge flows from patented university inventions are more widely distributed across assignees than those of firms) declined by over half between the early and late 1980s. Furthermore, unlike the decline in invention quality that occurred during the 1980s that Mowery et al found to be due to the entry of inexperienced universities, the increase in knowledge flow concentration we discover is largely driven by experienced universities; this finding suggests that the phenomenon we identify is unlikely to disappear with time but may actually increase as inexperienced universities become more like their experienced counterparts with respect to the manner in which they manage their intellectual property.

In addition to examining the pattern of knowledge flowing out from university inventions, we also study the pattern of flows *into* these inventions. Although the approach we employ to examine inflows is similar to the one we use to examine outflows, the phenomenon itself is distinct. Relative to firms, we expect universities draw from a wider set of prior art holders since academia is largely shielded from the anti-commons problem. This problem occurs when prior art is strongly enforced and widely distributed (Heller and Eisenberg (1998); Argyres and Liebskind (1998); David (2001); David (2003); Lessig (2002); Etzkowitz (1998); Krimsky (2003)).

Under these conditions, Cournot's "complements problem" can arise (Shapiro (2001)). Each upstream patent owner prices royalties without coordinating with owners of complementary patents. Without coordination, the marginal cost of utilizing complementary technologies is higher than if all patents were owned by a single agent. Moreover, a larger number of prior art holders may simply increase transactions costs incurred negotiating the rights to use the complementary technologies required to practice the invention (Ziedonis (2004)).

While firms may consciously conduct R&D with this in mind to minimize exposure to the anti-commons,[6] university researchers are largely insulated for two reasons. First, universities have traditionally been shielded from patent infringement liability due to the "experimental

[6]For example, from the outset of Kodak's efforts to develop its instant photography technology, the firm employed its legal counsel to work along with its R&D engineers to minimize the likelihood that any new technology would infringe on existing Polaroid patents (Warshofsky (1994); Rivette and Kline (2000); Jaffe and Lerner (2004)). In addition, Hall and Ziedonis (2001) and Ziedonis (2004) present evidence suggesting that firms building on prior art that is more fragmented patent more aggressively in order to facilitate cross-licensing and mitigate against potential infringement costs.

use exemption" (Eisenberg (2003)). Under this doctrine, otherwise infringing activity is permitted if it occurs "for amusement, to satisfy idle curiosity, or for strictly philosophical inquiry."[7] Second, to the extent that university researchers choose their research projects to advance knowledge and only concern themselves with patenting *ex post* – after something they have discovered is shown to work and offer commercial potential – their project selection and prior art decisions will not be influenced by concerns about potential hold-up during the subsequent product development phase.

However, as university patenting rises during the 1980s, we find that university researchers tend to draw from a more concentrated set of prior art holders. Specifically, our results suggest that the university diversity premium (the degree to which knowledge inflows used to develop patented university inventions are drawn from a less concentrated set of prior art holders than those used by firms) declined by over half between the early 1980s and early 1990s. Furthermore, similar to the case of knowledge outflows described above, the estimated increase in knowledge inflow concentration is driven by experienced universities, again suggesting that this phenomenon is not likely to dissipate with experience but may actually increase over time.

This finding may reflect a change over time in the manner in which university researchers conduct research. Rather than merely worrying about the patentability of an invention *ex post*, researchers may increasingly plan research projects with an eye towards commercialization. If motivated by pecuniary gains, as evidence reported by Lach and Schankerman (2005) suggests, academic researchers will look forward, anticipating the burden of future licensees, and reason backwards that the value of their intellectual property could be increased if they are able to plan their research approach so as to narrow the scope of prior art holders associated with complementary technologies.

Like Murray and Stern, our findings suggest caution with respect to the increasing ten-

[7] Walsh et al. (2005) present evidence suggesting that university researchers pay little attention to patents protecting research tools and are unlikely to modify their research due to impediments posed by existing patents. These findings are particularly interesting since they are based on data reflecting attitudes after the *Madey v. Duke* verdict of 2003.

dency to patent university research. However, our findings are quite distinct. Their paper shows the impact of patenting on knowledge dissemination: an overall reduction in the level of knowledge outflows. Our results suggest that, conditional on patenting and controlling for a reduction in overall flow levels, the management of knowledge flows both to and from universities has resulted in an increasing concentration of flows over time.

This behavior seems counter to the stated mandate of most US universities, which is often some permutation of maximizing the dissemination of new knowledge that results from their research. While the welfare implications of our findings are non-obvious - limiting access to new knowledge can be welfare enhancing if the welfare lost to those denied access is less than the welfare gained by those who are granted exclusivity to invest in commercialization (Colyvas et al. (2002); Mazzoleni (2005); Agrawal and Garlappi (2007)) - our results are consistent with the view that universities are increasingly managing their intellectual property like profit maximizing firms rather than as welfare maximizing public institutions.

These trends in university knowledge flows are important to identify and understand because they have real implications for science policy and economic growth. Precisely because of their non-commercial focus and their welfare enhancing objectives, universities play a unique and important role in the national innovation system (Nelson (1993); Nelson (1996)). They receive extensive government funding to produce basic knowledge that is intended to be widely disseminated.[8] It is in this context that universities have historically contributed to economic growth and welfare (Henderson et al. (1998)). To the extent that knowledge spillovers are indeed central to economic growth (Romer (1986); Romer (1990)), the finding that university flows, at least those associated with patented inventions, are narrowing throws into question the traditionally conceived arrangement between academia and society.[9]

[8]From 1980 to 1993, universities received approximately $103 billion (constant 1996 dollars) from all levels of government to fund basic R&D. This represents approximately 45% of all basic research undertaken in the US (National Science Board (2004)).

[9]As a current example of a public response to this trend, the National Institute of Health (NIH), a major US government funding agency, recently issued new guidelines urging universities to increase the frequency with which they license genomic, NIH-funded, patented inventions on a non-exclusive, rather than exclusive, basis (National Institute of Health (2005)).

The remainder of our paper proceeds as follows. In Section 2 we describe our empirical methodology, particularly the construction of our dependent variable, the "fragmentation index." In Section 3 we describe the patent citation data that we use to construct our measures. In Section 4 we present our empirical results for both knowledge outflows and inflows as well as provide examples to better understand the meaning of the estimated coefficients. Finally, in Section 5, we conclude by offering some possible explanations for our findings and directions for future research.

2 Methodology

Our empirical objective is to test whether knowledge flows associated with patented university inventions become more concentrated over time. Thus, most importantly, we need to employ an estimation technique that facilitates the clean identification of a change in the concentration of knowledge flows over time that is university-specific. Furthermore, we require an appropriate measure of knowledge flow concentration. We describe each of these in turn.

2.1 Estimation

In order to estimate university specific changes in concentration of knowledge flows over time, we analyze data from two distinct periods.[10] We define these as Period 1 (1980-1983) and Period 2 (1986-1989).[11] In order to identify changes in concentration that are university specific as opposed to general changes in flow patterns, we employ a difference-in-differences estimation (taking the difference of the change in concentrations over time between university versus firm patents). In addition, we include control variables to address specific dimensions

[10]As described in the introduction, we are interested in university-specific changes in the concentration of both knowledge outflows and inflows. Since the estimation procedure is almost identical, we describe the outflows case only and comment in footnotes where the methodology differs for inflows.

[11]In the case of knowledge inflows, we define Period 2 as 1990-1993 since we use backward citations and thus are not restricted by the data set ending in 1999.

along which it is plausible that universities systematically patent differently than firms (e.g., inventions that are more important, more basic, or more likely from a particular technology field).

Thus, we estimate the following relationship:

$$Frag_p = F(\alpha_o + \alpha_1 D_p + \alpha_2 ERA_p + \alpha_3 D_p ERA_p + X_p \alpha_4 + X_p ERA_p \alpha_5) + \varepsilon_p \tag{1}$$

where $Frag_p$ measures the fragmentation of ownership dispersion of patents building upon patent p ("forward fragmentation" of knowledge outflows).[12] D_p is a university dummy variable that takes a value of one if p is assigned to a university and zero otherwise. ERA_p identifies patents that were issued in Period 2 (i.e., $ERA_p = 1$ if patent p was issued in 1986-1989 and zero otherwise).[13] X_p is a vector of variables that control for non-institutional factors that may also affect fragmentation. Finally, ε_p is a mean zero random error.

We use Equation 1 to test whether the university dummy explains some of the fragmentation of knowledge flows, $Frag_p$. The sign and significance of $\hat{\alpha}_1$ offers insight into the relationship between institution type and the patterns of related knowledge flows. If $\hat{\alpha}_1$ is such that the marginal effect of the university dummy is positive,

$$F(\hat{\alpha}_o + \hat{\alpha}_1 + X_p \hat{\alpha}_4) - F(\hat{\alpha}_o + X_p \hat{\alpha}_4) > 0,$$

and statistically significant we will interpret this as suggestive evidence that university knowledge flows are less concentrated than those of firms, at least in Period 1.[14] This finding would be consistent with our prior beliefs about the differences between university and firm knowledge flows.

To identify how any initial difference in knowledge flows between universities and firms

[12] Similarly, for the case of knowledge inflows, $Frag_p$ measures the fragmentation of prior art holders upon which patent p builds (backward fragmentation).

[13] For the case of knowledge inflows, the dummy variable ERA_p distinguishes patents that were *applied* for in Period 2 (i.e., $ERA_p = 1$ if patent p was submitted to the patent office in 1990-1993 and is zero otherwise).

[14] In this case, $ERA_p = 0$ because we are analyzing patents in Period 1.

have changed over time, we focus on $\hat{\alpha}_3$, the coefficient on the interaction between the university dummy variable, D_p, and ERA_p. If $\hat{\alpha}_3$ is such that,

$$\left[F(\hat{\alpha}_o + \hat{\alpha}_1 + \hat{\alpha}_2 + \hat{\alpha}_3 + X_p\hat{\alpha}_4 + X_p\hat{\alpha}_5) - F(\hat{\alpha}_o + \hat{\alpha}_2 + X_p\hat{\alpha}_4 + X_p\hat{\alpha}_5)\right]$$

$$-\left[F(\hat{\alpha}_o + \hat{\alpha}_1 + X_p\hat{\alpha}_4) - F(\hat{\alpha}_o + X_p\hat{\alpha}_4)\right] < 0,$$

we will interpret this as indicating that the change in the difference between university and firm knowledge dispersion over time is negative; in other words, knowledge flows from university patents have become disproportionately more concentrated.

2.2 Variables

We construct each of our variables using information found on the front page of the patents in our data. When a patent is issued, a substantial amount of information regarding the innovation embodied by the patent is disclosed, including the technology field,[15] the assignee name (i.e., the patent's owner), and all prior patents on which the given innovation builds (i.e., prior art citations). These citations are important for our study because they trace the knowledge flows between patents;[16] they may also indicate complementary technologies that

[15] Technology fields are determined by the US Patent and Trademark Office (USPTO) and are analogous to industry classes in an industry classification system such as the Standard Industrial Classification (SIC). Technology classes, however, do not map readily to any one industry because a given innovation can be applied in a wide range of industries. See Kortum and Putnam (1997) for details regarding technology field-industry concordances.

[16] We use patent citations as a proxy for knowledge flows. However, citations are not straightforward to interpret in terms of direct knowledge flows, and the signal-to-noise ratio for this measure is therefore likely to be rather low. Patents cite other patents as "prior art," with citations serving to delineate the property rights conferred. Some citations are supplied by the applicant, others by the patent examiner, and some patents may be cited more frequently than others because they are more salient in terms of satisfying legal definitions of prior art rather than because they have greater technological significance. Cockburn et al. (2002) report, for example, that some examiners have "favorite" patents that they cite preferentially because they "teach the art" particularly well. Nonetheless, Jaffe et al. (2002) surveyed cited and citing inventors to explore the "meaning of patent citations" and found that approximately one-quarter of the survey responses corresponded to a "fairly clear spillover," approximately one-half indicated no spillover, and the remaining quarter indicate some possibility of a spillover. Based on their survey data, the authors conclude: "We believe that these results are consistent with the notion that citations are a noisy signal of the presence of spillovers. This implies that aggregate citation flows can be used as proxies for knowledge-spillover intensity, for example, between categories of organizations or between geographic regions" (p. 400).

may need to be used to practice the invention.[17] As such, while a patent grants the assignee the right to exclude others from practicing the invention described in the patent, it does not necessarily grant the owner the right to practice the invention without the permission of cited assignees. Consequently, citing assignees can be used as a proxy for potential licensees. As indicated by Ziedonis (2004) and Rivette and Kline (2000), this is how some IP consulting firms have come to use citations.[18]

2.2.1 Dependent Variable

Our dependant variable, a measure of the concentration of knowledge flows, is constructed in the spirit of the "fragmentation index" developed in Ziedonis (2004). Again, we describe only the knowledge outflows measure, or forward fragmentation, $ForFrag_{i,p}$, given that the backward measure, $BackFrag_{i,p}$ is defined analogously using the citations a patent makes rather than receives.

Forward fragmentation measures the ownership dispersion of subsequent patents that cite a focal patent. Specifically, for a focal patent p issued to assignee i, the fragmentation measure $ForFrag_{i,p}$ is given by:

$$ForFrag_{i,p} = \left[1 - \sum_{j \in J} \left(\frac{C_{j,i,p}}{C_{i,p}}\right)^2\right] \frac{C_{i,p}}{C_{i,p} - 1}, \tag{2}$$

where J is the set of assignees whose patents cite the focal patent, $i \notin J$, and $C_{j,i,p}$ are all citations made to p by patents belonging to assignee $j \in J$. In Equation 2, $C_{i,p}$ is the total number of patents citing patent p that do not belong to i. That is:

$$C_{i,p} = \sum_{j \in J} C_{j,i,p}. \tag{3}$$

Our fragmentation variable simply measures dispersion as the expected probability that

[17]This point is made in Ziedonis (2004).

[18]These firms use citations to assess potential licensees and to determine what patents are best to renew or to allow to lapse.

two randomly selected citations made to a given patent refer to citing patents issued to two *different* assignees.[19,20] Consequently, the measure's range of possible values is the unit interval. For patents that have more widely distributed knowledge outflows (i.e., higher fragmentation), the probability that any two sampled citations belong to different assignees will be closer to one. Conversely, the probability of this event will be closer to zero the more concentrated the citing intellectual property is.

To gain a better intuition for interpreting this dispersion index, which is related to the familiar Herfindahl concentration measure, consider the following three examples of focal patents that are each cited by 10 patents (i.e., $C_{i,p} = 10$). First, suppose the focal patent is cited by 10 patents that are all issued to IBM, $J = \{IBM\}$. In this case, citing patents are perfectly concentrated and thus make it impossible for any two citations to refer to different assignees, $ForFrag_{i,p} = 0$. Next, suppose the focal patent receives five citations each from two different assignees. This yields an intermediate measure of fragmentation; the probability that any two of the 10 citations are made by different assignees is approximately half, $ForFrag_{i,p} \simeq 0.556$.[21] Finally, suppose the focal patent is cited once each by 10 different

[19]This is a traditional interpretation for dispersion measures of the type defined by Equation 2. See Easterly and Levine (1997) for an example of this interpretation in the context of measuring ethnic diversity.

[20]With this interpretation, one can easily understand the fragmentation measure defined by Equation 2. Due to the count nature of citations (i.e., too few citations are typically made to make sampling with replacement an appropriate assumption), the conditional probability that two citing patents belong to different assignees, given that one of these two citations is known to belong to assignee j, is:

$$1 - Pr(\text{Second citation belongs to assignee } j) = 1 - \frac{C_{j,i,p} - 1}{C_{i,p} - 1}.$$

Consequently, the expected probability that two randomly chosen citing patents belong to different assignees is:

$$\sum_{j \in J} \frac{C_{j,i,p}}{C_{i,p}} \left(1 - \frac{C_{j,i,p} - 1}{C_{i,p} - 1}\right) = 1 - \sum_{j \in J} \frac{C_{j,i,p}}{C_{i,p}} \frac{C_{j,i,p} - 1}{C_{i,p} - 1}.$$

It can then be shown that

$$1 - \sum_{j \in J} \frac{C_{j,i,p}}{C_{i,p}} \frac{C_{j,i,p} - 1}{C_{i,p} - 1} = \left\{1 - \sum_{j \in J} \left(\frac{C_{j,i,p}}{C_{i,p}}\right)^2\right\} \frac{C_{i,p}}{C_{i,p} - 1}.$$

The term $\frac{C_{i,p}}{C_{i,p}-1}$ in Equation 2 corrects the empirical probability had we assumed that we could sample with replacement. Without this adjustment, our dispersion measure would be biased toward zero. This is the same adjustment recommended by Hall et al. (2002).

[21]$Forfrag_{i,p} = (1 - 2(\frac{5}{10})^2)\frac{10}{9} \simeq 0.556$.

assignees. In this case, it is certain that any two citations will come from different assignees, $ForFrag_{i,p} = 1$.

2.2.2 Control variables

Our identification of university specific fragmentation is based on a difference-in-differences estimation that compares differences in fragmentation over time between universities and firms. This approach is used to "difference out" overall changes in knowledge flow fragmentation that are not university specific. However, it may be the case that identified changes in university knowledge flow fragmentation are the result of certain characteristics of university patents rather than institutional characteristics of universities themselves. For example, it may be the case that the probability of generating a "general purpose" patent increased less over time for universities than for firms and that general purpose patents are more likely to generate diffused knowledge outflows due to their wide applicability. This could appear as a university specific increase in knowledge flow concentration over time, but is actually a "generality" effect rather than an institutional effect caused by a change in the management practices of university intellectual property. Similarly, it may be the case that the probability of generating a biotechnology patent increased more over time for universities than firms and that biotechnology patents are more likely to generate concentrated knowledge outflows. Again, this could appear as a university specific increase in knowledge flow concentration over time but is actually a biotechnology effect.[22]

We control for these and several other possible confounding effects. Specifically, we control for four invention specific characteristics: 1) generality, 2) technology field, 3) importance, and 4) university science.[23] First, "generality" is constructed using the same citations used to

[22] We acknowledge that universities might manage their entire patent portfolio in a manner that influences knowledge flow concentration. However, our analysis focuses on how universities manage patents individually. For example, over time a university might allocate technology transfer resources more heavily towards a particular field, such as biotechnology. If biotechnology patents generate more concentrated knowledge flows, this would affect our dependent variable but the variance would be captured by the technology field coefficient rather than the coefficient of interest, the coefficient on the university dummy. Thus, we may underestimate the university management effect.

[23] In the case of inflows, we control for "originality" rather than generality and "citations made" rather

calculate the dependant variable. However, rather than measuring the dispersion of citations received from different assignees, this control measures dispersion of citations received from different technology fields defined by the US Patent and Trademark Office (USPTO) three-digit technology classification system.[24]

Second, we include technology field fixed effects using dummy variables coinciding with the NBER two-digit technology field classification.[25] Third, we control for invention importance using a simple count of total citations received by the focal patent.[26] Finally, we control for the degree to which a patent is cited by universities as a factor influencing fragmentation. We control for this with a variable representing the share of citations received from university patents. This variable controls for any systematic "university science" effect that might induce innovators to be cited by a smaller (or larger) group of assignees (i.e., universities).

3 Data

We collect our data primarily from the NBER patent database described by Hall et al. (2002). This source provides all the raw citation data needed to construct the variables in our samples. In addition, we use the report "US Colleges and Universities-Utility Patent Grants, Calendar Years 1969-2000"[27] to identify all US university patents granted from 1969 to 1999.[28]

than importance. These measures are similar in spirit.

[24] "Generality" reflects the extent to which the knowledge embedded in a focal patent is applicable across other technology fields (Trajtenberg et al. (1997)).

[25] Our conclusions are robust to using more disaggregated technology field fixed effects; dummy variables based on the USPTO three-digit technology classification codes do not change our conclusions.

[26] The generality and importance measures, as described in Hall et al. (2002), have been widely used in the patent-based economics of innovation literature.

[27] This source is produced by the Information Products Division, Technology Assessment and Forecast Branch (2002).

[28] When referring to universities, we refer to universities, colleges, polytechnics, other post-secondary institutions, and university consortia.

3.1 Sample Construction

Since we ask two different but related questions concerning changes in the concentration of university knowledge outflows and university knowledge inflows, we require two distinct samples. Although the sample construction process used for each is similar, there are a few key differences. Thus, we describe each separately below.

3.1.1 Knowledge Outflows Sample

This sample is composed of a subset of all utility patents issued to US non-government organizations by the USPTO.[29] Specifically, we collect patents issued during the periods 1980-1983 and 1986-1989. This results in 241,929 patents. Furthermore, of this set of patents, we only keep those that receive at least two citations since our forward fragmentation and generality measures are undefined otherwise.[30,31]

Next, we define the specific citations we consider. We ignore self-citations because we are interested in how knowledge flows between agents in the economy.[32] Furthermore, we do not consider citations received from patents applied for before the focal patent was issued. We do this because we assume that citations from such patents are unlikely to represent knowledge flows due to the secrecy usually maintained during the patenting process. Finally, due to truncation issues, we remove citations that come from patents issued more than 10 years after the focal patent issue date.[33] Consequently, by only keeping patents that receive at least two "allowable" citations, we are left with a final sample containing 173,499 focal patents that

[29] A utility patent is a patent protecting a process, machine, composition of matter, or an improvement of any one of these things.

[30] This is obvious from the definition of our forward fragmentation measure defined in Equation 2.

[31] It is difficult to deduce what bias these exclusions introduce into our results. Other studies that use these measures confront similar problems (e.g., Mowery et al. (2004)). Thus, it is important to note that our results may only apply to patents that receive at least two citations and, in the case of inflows, to patents that make at least two citations.

[32] A self-citation is a citation received from a patent issued to the same assignee as the focal patent.

[33] We choose 10 years since the NBER patent database contains citation data up to 1999. Since our focal patents can be issued as early as 1980 and as late as 1989, the earlier patents would have nine more years to accumulate citations if we did not truncate our citation window to 10 years. Since we focus on the difference-in-differences estimation, this issue is likely less of a problem, but we truncate the data in case university patents differ systematically from firm patents along this dimension.

are, on average, referenced by 7.88 citing patents.

3.1.2 Knowledge Inflows Sample

This sample is also composed of a subset of all USPTO utility patents issued to US non-government organizations. In this case we collect patents *applied* for during 1980-1983 and 1990-1993. This results in 289,894 focal patents. Next, similar to the outflows sample construction, we remove patents that do not make at least two citations since our dependant variable, $BackFrag$, as well as our measure of originality are undefined for these patents.

Thus, by construction, each focal patent in our sample cites at least two patents. Moreover, as in the earlier case, we only consider citations with particular characteristics. Since we are concerned about potential anti-commons effects on knowledge inflows, we only consider cited patents that can potentially hold-up the utilization of follow-on inventions. Therefore, we focus on cited patents not owned by the focal assignee and that were issued before (but no more than 10 years before) the application of the focal patent. We consider these citations because they are particularly salient in terms of potential for impeding the utilization of the new invention.[34] Removing focal patents that make less than two "allowable" citations, we generate a final sample that includes 201,433 focal patents that, on average, cite 5.79 prior patents.

3.2 Data limitations

Though rich, our data has limitations. Most notably, some of the patents in the data do not include assignee information. This is important since our dependent variable, the fragmentation index, is constructed using this information.[35] As described in Hall et al.

[34]For example, an IBM patent applied for in 1980 might cite a Texas Instrument patent issued in 1969, an Intel patent issued in 1973, an IBM patent issued in 1978, and an AMD patent issued in 1981. Of these cited patents, we remove all but the Intel patent because it is less than 10 years old and so is likely to remain enforced by the time the focal invention is practiced and because it is not owned by IBM. Furthermore, unlike the AMD patent, the Intel patent was issued early enough that it could be observed by IBM and thus could have influenced IBM's decision to develop and ultimately patent the focal invention.

[35]For example, when calculating the forward fragmentation measure, we need to know ownership information for the focal patent and for each of the citing patents.

(2002), 18.4% of all patents in the NBER database have unidentified owners.

However, we take a number of steps to minimize this problem. First, by construction, we only use focal patents for which we have assignee information. Recall that our initial set of patents is drawn from patents issued to US non-government organizations. Thus, only our citing patents may be missing assignee information.[36] Next, since we apply a 10-year window for constructing our backward fragmentation index and older patents are more likely to be missing assignee information, we further limit our exposure to this problem.

In addition, we utilize inventor name data that is also provided by the NBER database.[37] We use this information to obtain a better measure of fragmentation for patents that are cited by more than one unassigned patent. In these cases, we group the unassigned citations by the first inventor of the unassigned patents. For example, if a sampled patent cites two unassigned patents, both with the same first inventor, we treat these two citations as belonging to the same assignee.

Thus, as a result of these measures, only 13.3% of the citations made by our sampled patents are to unassigned patents and only 12.0% of citations received are from unassigned patents. Alternatively, each sampled patent, on average, cites 0.80 unassigned patents and receive 0.85 citations from unassigned patents. Finally, when calculating our fragmentation measure, we assume unassigned patents are not self-citations and that each belongs to a different assignee. However, as a robustness check, we also estimate our key models using fragmentation measures constructed by instead assuming that all unassigned patents belong to a single assignee; our results do not change. In addition, we further check robustness by limiting our sample to only those focal patents that are cited by patents with full assignee information; our results persist.[38]

A second limitation of the data is the absence of ownership transfer information. Our fragmentation measure is calculated based on the assignee identified at the time each patent is

[36] Similarly, for the knowledge inflows case, only our cited patents may be missing assignee information.

[37] The NBER patent database provides the inventor name(s) for all patents issued after 1974.

[38] We similarly check robustness for the knowledge inflows case by limiting our sample to only those focal patents that cite patents with full assignee information, and again our results persist.

issued. However, Serrano (2005) finds that the sale and purchase of patents is not uncommon. This would only pose a problem if the likelihood of ownership transfer (specifically the type that would cause a change in fragmentation) changed at a different rate for universities than firms. The literature on this topic is limited and does not indicate whether this is the case. Moreover we do not have access to ownership transfer data to check; thus, we note this as a caveat for interpreting our results and an issue warranting further research.

4 Results

4.1 Summary Statistics

We present summary statistics on Table 1 confirming the findings of Henderson et al. (1998) that university patents are more important, general, and original than firm patents. Beginning with Panel A, which presents data for the knowledge outflows sample, we see that university patents are more important (they receive more citations) in both Periods 1 and 2. For example, the average university patent receives 35% more citations than the average firm patent in Period 1 and 32% more citations in Period 2. Similarly, university patents are more general in both periods. Turning to Panel B, we see that university patents are also more original, and this difference seems to increase over time.

Next, we consider our variable of interest - the fragmentation index. Beginning with Panel A, we see that knowledge outflows from university patents are more fragmented than their private sector counterparts in Period 1. (We explain how to interpret the difference in index values in Section 4.4.) However, this difference seems to disappear by Period 2. Similarly, in Panel B, we see that knowledge inflows to university patents are more fragmented than those to firm patents in Period 1. Again, however, this difference seems to disappear by Period 2.

Although these statistics are suggestive of a change in university behavior concerning the management of knowledge flows associated with patented inventions, changes in institution-related fragmentation measures could be confounded with changes in non-institutional factors (such as technology field portfolio) as we note in the methodology section above. Thus, we turn next to regression analysis, which allows us to control for key invention characteristics.

4.2 Regression Analysis: Dispersion of Knowledge Outflows

We report the estimated OLS coefficients of Equation 1 for the knowledge outflows sample in Table 2. Recall that the dependent variable in this case is $ForFrag_{i,p}$. Referencing the fully specified model reported in Column IV, we see from the estimated coefficient on the university dummy that university patents in Period 1 are more fragmented than their private sector counterparts, even after controlling for the importance, generality, and technology field of the invention. We refer to this difference – the degree to which knowledge flows from patented university inventions are more widely distributed across assignees than those of firms – as the university diffusion premium.

Turning to the coefficient on the interaction between the university dummy and the Period 2 dummy (ERA), we see that the university diffusion premium is significantly diminished by the second period. In fact, by comparing the magnitudes of this coefficient with the coefficient on the university dummy (with no interaction), we see that the university diffusion premium measured in Period 1 is reduced by approximately 74% by Period 2. By comparison, other characteristics of university patents, such as their tendency to be more general than firm patents, remain virtually unchanged over this period.

This is our main result with respect to the increasing concentration of knowledge outflows from university patents. We check for robustness in a number of ways. First, we show that the result holds in various specifications of Equation 1, which are also reported in Panel A of Table 2. We also confirm that the result holds using different procedures for handling unassigned patents.[39] Furthermore, the result holds when we use finer technology class fixed effects based on the USPTO three-digit classification system. Finally, due to the nature of the dependent variable, we estimate Equation 1 using Fractional Logit rather than OLS.

[39] Specifically, we treat all unassigned patents as if they are from the same assignee and, separately, we drop all observations for which one or more of the citing patents is unassigned. The result is robust.

Again, the result holds. We discuss the details of this next.

4.2.1 Fractional Logit

Although coefficients estimated using OLS are straightforward to interpret, this regression method may not be suitable since our dependent variable is an index that only takes values between zero and one. However, due to its linear nature, OLS estimation can yield predictions that are negative or greater than one. Thus, fractional logit regression, as described by Papke and Wooldridge (1996), may be more suitable.

To implement this estimation technique, we assume a logistic functional form for the conditional mean of our fragmentation measure. More explicitly, we assume:

$$E[ForFrag_p|D_p, ERA_p, X_p] = \frac{\exp\{\alpha_o + \alpha_1 D_p + \alpha_2 ERA_p + \alpha_3 D_p ERA_p + X_p\alpha_4 + X_p ERA_p \alpha_5\}}{1 + \exp\{\alpha_o + \alpha_1 D_p + \alpha_2 ERA_p + \alpha_3 D_p ERA_p + X_p\alpha_4 + X_p ERA_p \alpha_5\}}.$$

Given this assumption, the parameters are estimated by quasi-maximum likelihood estimation, where the quasi-log likelihood, l_p, for a given observation p is:

$$l_p = Frag_p \log\left\{\frac{\exp\{\alpha_o + \alpha_1 D_p + \alpha_2 ERA_p + \alpha_3 D_p ERA_p + X_p\alpha_4 + X_p ERA_p \alpha_5\}}{1 + \exp\{\alpha_o + \alpha_1 D_p + \alpha_2 ERA_p + \alpha_3 D_p ERA_p + X_p\alpha_4 + X_p ERA_p \alpha_5\}}\right\}$$

$$+(1-Frag_p)\log\left\{1-\frac{\exp\{\alpha_o + \alpha_1 D_p + \alpha_2 ERA_p + \alpha_3 D_p ERA_p + X_p\alpha_4 + X_p ERA_p \alpha_5\}}{1 + \exp\{\alpha_o + \alpha_1 D_p + \alpha_2 ERA_p + \alpha_3 D_p ERA_p + X_p\alpha_4 + X_p ERA_p \alpha_5\}}\right\}.$$

Using this procedure yields estimates that must take values within the unit interval.

Panel B in Table 2 provides the marginal effects of each variable specified in Equation 1 based on coefficients estimated with fractional logit regressions.[40] Evaluated at the sample mean, the marginal effect of each variable is very close in magnitude and significance to the

[40] It is important to note that the marginal effects are not simply given by the coefficients estimated in our fractional logit regressions. Since we assume a non-linear functional form for the conditional mean of the dependant variable, we calculate the marginal effects as suggested by Ai and Norton (2003). Furthermore, to remain consistent with the exposition of the OLS estimates, the estimated marginal effects of variables not interacted with the ERA_p variable show the marginal effects these variables had on fragmentation in Period 1. The marginal effect of interacted variables show the change in the marginal effect from Period 1 to Period 2.

OLS estimates.[41]

4.2.2 Experience and Dispersion of Knowledge Outflows

The rapid rise in university patenting that occurred during the 1980s reflects significant change in the overall landscape with respect to academia's approach to the management of intellectual property. During this period, many universities that did not have a formal technology transfer office established one and created standardized procedures for managing the disclosure, patenting, and licensing process (Mowery et al. (2004)). In addition, much of the increase in patent activity came from "inexperienced" institutions that had been issued few patents prior to 1980.

The increasing role of these inexperienced institutions in university patenting influenced the overall character of the "average" university patent. Indeed, the decrease in importance and generality of university patents over time identified by Henderson et al. (1998) was shown by Mowery et al. (2004) to be due to the entry of inexperienced schools. The implication of the Mowery et al. finding is very important; since the measured decrease in importance and generality was due to the entry of inexperienced universities, the effect was likely temporary while these schools learned to manage their intellectual property to become more like their experienced counterparts.

Since our study is similar in spirit to these papers, it is incumbent upon us to also check whether our effect is a result of entry by inexperienced universities. To accomplish this we categorize our university patents in a similar way to Mowery et al. We divide universities into two categories based on their patenting experience prior to 1981. We define: (1) High Experience Universities as those universities obtaining at least 10 patents that were applied for after 1970 but before 1981, and (2) Low Experience Universities as those universities that obtained less than 10 patents that were applied for during the same period.[42] Based on this

[41] Similar results follow when we use double-sided tobit regressions.

[42] Though our categorization of universities is similar to Mowery et al. (2004), it is not identical. Specifically, we do not distinguish between the less experienced institutions. Whereas Mowery et al. delineates between universities with moderate experience (universities that obtained between one to nine patents that were

categorization, experienced universities account for 87% (984) and 72% (1948) of the focal university patents in Periods 1 and 2, respectively.

To examine the effects of experience on knowledge outflows, we run essentially the same regressions as in Table 2. The only difference is that we now break apart the university effect according to the level of university experience. We do this by using two university dummy variables that differentiate between universities according to the categories of experience described above.

The regression results in Table 3 show that the reduction in the breadth of knowledge from university patents estimated in the prior section is not driven only by the entry of inexperienced universities. In fact, the coefficient on the interaction dummy (High experience university * ERA) is highly significant. This result suggests that the issue of interest, an increase in the concentration of knowledge flows associated with university patents, is at least partly driven by experienced universities implying that, unlike the decline in importance and generality, this is not likely a temporary phenomenon.

4.3 Regression Analysis: Diversity of Knowledge Inflows

We turn next to examine the concentration of knowledge *inflows*. Although the economic forces affecting the concentration of inflows are different from those affecting that of outflows, as we described in the introduction, the econometric approach to identifying changes in concentration is much the same.

We report the estimated coefficients of Equation 1 for the knowledge inflows sample in Table 4. Recall that the dependent variable in this case is $BackFrag_{i,p}$. Referencing the fully specified model reported in Column IV, we see from the estimated coefficient on the university dummy that university patents in Period 1 are more fragmented than their private

applied for after 1970 but before 1981) and universities without experience (universities with zero patents applied for during this time), we group these two categories into one. Also, our categorization differs slightly for two measurement reasons: (1) we only consider those patents that made at least two citations while Mowery et al. considers all university patents; and (2) we include patents applied for by the University of California, Stanford University and Columbia University while Mowery et al. excludes these universities.

sector counterparts, even after controlling for the originality, technology field, and overall number of citations made. We refer to this difference – the degree to which knowledge inflows used to develop patented university inventions are drawn from a less concentrated set of prior art holders than those used by firms – as the university diversity premium.

Turning to the coefficient on the interaction between the university dummy and the Period 2 dummy (ERA), we see that the university diversity premium is significantly diminished by the second period. In fact, by comparing the magnitudes of this coefficient with the coefficient on the university dummy (with no interaction), we see that the university diversity premium measured in Period 1 is reduced by approximately 67% by Period 2. By comparison, another characteristic of university patents, their tendency to be more original than firm patents, does not diminish but rather is further amplified over this period.

This is our main result with respect to the increasing concentration of knowledge inflows. As before, we check for robustness in a number of ways. First, we show that the result holds in various specifications of Equation 1, which are also reported in Panel A of Table 4. In addition, we estimate Equation 1 using Fractional Logit rather than OLS. The results presented in Panel B are very similar to those generated by OLS.[43] We also confirm that the finding holds using the different procedures for handling unassigned patents described above. Furthermore, the result holds when we use finer technology class fixed effects based on the USPTO three-digit classification system.

4.3.1 Experience and the Dispersion of Knowledge Inflows

For the reasons outlined in Section 4.2.2 above, we must check whether the decline in the university diversity premium measured here is the result of entry by institutions that were less experienced at managing intellectual property. Recall that this issue is important since if the decline is due to the entry of inexperienced universities, the effect is likely temporary while these schools learn to manage their intellectual property like their experienced counterparts.

[43] Similar results follow when we use double-sided tobit regressions.

As before, we define the universities in our data as either high or low experience. Based on this categorization, experienced universities account for 81% (982) and 61% (2694) of the focal university patents in Periods 1 and 2, respectively.

To examine the effects of experience on knowledge inflows, we run essentially the same regressions as in Table 4. The only difference is that we again break apart the university effect according to the level of university experience. We do this by using two university dummy variables that differentiate between high and low experienced universities.

The regression results in Table 5 show that the reduction in diversity of knowledge sources used in developing patented university inventions estimated in Section 4.3 is not driven only by the entry of inexperienced universities. In fact, the coefficient on the interaction dummy (High Experience university * ERA) is highly significant. While the negative value of the interaction coefficient is slightly greater for inexperienced universities in terms of magnitude, it is not significant at the 10% level, whereas the coefficient on the interaction term for experienced universities is significant at the 5% level. Most importantly though, this result suggests that the issue of interest, an increase in the concentration of knowledge flows into university patents, is at least partly driven by experienced universities, suggesting that this is not likely a temporary phenomenon.

4.4 Interpretation of Fragmentation Index Values

The meaning of the fragmentation index, the basis of our dependent variables, can be difficult to comprehend. Similar to the Herfindahl index, which, although often used in market concentration studies is usually accompanied by more intuitive "four firm concentration ratios," the fragmentation index is complex. This is because many states of the world (e.g., combinations of citation frequencies and assignee distributions) can generate similar values. Although the index is complicated, however, it is important to understand. Throughout most of the discussion so far, we have described changes in university knowledge flow concentration in relative terms. In other words, we have discussed the change in the university premium rather than the absolute change in the concentration of university knowledge flows. While the relative change in concentration between periods seems large (> 50%), the absolute change seems small (< 3%). Ultimately, we are interested in whether the change is economically important. To this end, we offer three distinct ways of interpreting the fragmentation index to help the reader develop intuition for comprehending the economic significance of the estimated changes in knowledge flow concentrations.

4.4.1 Distribution of Assignees across a Single Patent

Consider a patent that receives eight citations, roughly the mean number of citations received by focal patents in our sample. Further, suppose these citations are from five different assignees. If three different assignees each cite the patent twice while the remaining two assignees only cite the patent once, then the fragmentation measure equals 0.89.[44] To increase the fragmentation measure by 0.04 (approximately the value of the coefficient on the university dummy) while holding constant the total number of citations, one additional assignee would have to cite the patent (now six unique assignees, rather than five). In this case, two assignees would each cite the patent twice while four would each cite the patent once. With this distribution, the fragmentation would increase to about 0.93.[45]

4.4.2 Distribution of Average versus Perfectly Concentrated Patents

Suppose there are two periods in which university patents are issued: Period 1 and Period 2. Further suppose that all Period 1 patents are average in terms of concentration (i.e., they have the average fragmentation value). However, in Period 2, patents are either average or perfectly concentrated (i.e., $fragmentation = 0$). To develop intuition for interpreting the meaning of our estimated coefficients, we calculate what fraction of patents must be perfectly concentrated in order to obtain the observed drop in the average fragmentation value from Period 1 to Period 2.

[44] $ForFrag_p = \{1 - \frac{2}{64} - 3\frac{2^2}{8^2}\}\frac{8}{8-1} \simeq 0.89$
[45] $ForFrag_p = \{1 - \frac{4}{64} - 2\frac{2^2}{8^2}\}\frac{8}{8-1} \simeq 0.93$

Specifically, we use the fractional logit procedure to estimate the relationship between a patent's fragmentation, $frag_p$, and the same patent's characteristics, (ERA_p, X_p):

$$frag_p = F(\alpha_o + \alpha_1 ERA_p + X_p\beta) + \varepsilon_p.$$

Note that, for simplicity, no variable is interacted with the period effect, ERA_p, as was done in the specifications reported earlier. Here we assume the relationship between all control variables and $frag_p$ does not change over time.

To estimate the absolute decrease in fragmentation, Δ, we find the estimated marginal effect of ERA_p. Since ERA_p is a dummy variable that equals one for any patent, p, in Period 2 and zero otherwise, the marginal effect is given by:

$$\Delta = F(\hat{\alpha}_o + \hat{\alpha}_1 + \overline{X}\hat{\beta}) - F(\hat{\alpha}_o + \overline{X}\hat{\beta}).$$

Δ is calculated at the sample mean, $\overline{X}$, to remain consistent with the estimated marginal effects found in the main tables above.

Finally, since patents in Period 2 can only have a fragmentation value equal to $F(\hat{\alpha}+\hat{\beta}\overline{X})$ (the "average" level of fragmentation in the Period 1) and zero (perfectly concentrated flows), we need to determine the number of patents, Y, out of a total of T patents in Period 2 that must have perfectly concentrated knowledge flows to cause the change in average fragmentation, Δ. That is, we solve:

$$\frac{(T-Y)F(\hat{\alpha}_o + \overline{X}\hat{\beta}) + (Y)0}{T} - F(\hat{\alpha}_o + \overline{X}\hat{\beta}) = \Delta,$$

or

$$\frac{Y}{T} = -\frac{\Delta}{F(\hat{\alpha}_o + \overline{X}\hat{\beta})}.$$

Recalling that in Period 1 all university patents have fragmentation equal to $F(\hat{\alpha}_o + \overline{X}\hat{\beta})$ implies that the propensity of patents with perfectly concentrated knowledge flows increased from 0 to $\frac{Y}{T}$.

Thus, from Table 6 we see that our estimated changes imply the following. For the knowledge outflows case, if there are 100 patents in Period 1 that all have the average level of fragmentation, in Period 2 approximately 96 will still have the average level of fragmentation, while four will be perfectly concentrated (i.e., all citations come from a single assignee). For the knowledge inflows case, only one patent will be perfectly concentrated. Clearly, the estimated changes in concentration are likely not the result of perfect concentration (i.e., rather than 4% of the focal patents being perfectly concentrated, a larger percentage might be moderately more concentrated than average) but this simple dichotomy allows for developing intuition regarding the economic implications of our findings.

4.4.3 Distribution of Average Firm versus Perfectly Fragmented Patents

In our final illustrative example, we compare university patents to those of firms. Suppose all firm patents have the same level of fragmentation, $\overline{Frag_f}$. Suppose also that university patents can take two values of fragmentation, either $\overline{Frag_f}$ or one (the latter case implies perfect fragmentation such that all citations come from unique assignees). Our data indicate that the average fragmentation of university patents, $\overline{Frag_u}$, is greater than that of firm patents such that $\overline{frag_u} = \overline{frag_f} + \Delta$ where $\Delta > 0$.

In this example, we ask, given the assumptions described above, what must the distribution of university fragmentation be (i.e., proportion where fragmentation is $\overline{Frag_f}$ versus 1) to generate an average level of fragmentation that is Δ greater than that of firm patents? We address this with a simple exercise.

Randomly draw T university patents. Let Y be the number of these T patents with fragmentation equal to 1 and consequently T-Y is the number of patents with fragmentation equal to $\overline{Frag_f}$. Thus, we want to know: What fraction of the university patent sample (i.e., $\frac{Y}{T}$) must have a fragmentation equal to one such that the average university fragmentation is greater than the average firm fragmentation by Δ. That is, what does $\frac{Y}{T}$ have to be such that

$$\overline{Frag}_u = \frac{Y + (T - Y)\overline{Frag}_f}{T} = \overline{Frag}_f + \Delta?$$

The solution is:

$$\frac{Y}{T} = \frac{\Delta}{1 - \overline{Frag}_f}.$$

Given our estimates of the coefficients on the university dummy variables and the sample fragmentation means for firm patents, we find the following for knowledge outflows (i.e., forward fragmentation). Initially, in Period 1, university fragmentation is greater by about 0.027 (the estimated value of the university dummy variable in Table 2 Column (VIII)) and the sample mean of firm fragmentation is 0.879 (i.e., the sample mean of firm patents in Period 1, shown in Table 1). This implies that 22 out of 100 university patents are perfectly fragmented in Period 1 compared to only six in Period 2.[46]

For knowledge inflows, we use the estimated initial fragmentation difference between firm and university patents, which is 0.02 (the estimated value of the university dummy variable in Table 4 Column (VIII)) and the sample mean of firm fragmentation of 0.903 (the sample mean of firm patents in Period 1 shown in Table 1). Using these values, we calculate that approximately 21 out of 100 university patents are perfectly fragmented in Period 1 compared to only seven in Period 2.[47]

5 Conclusion

The dramatic rise in the level of university patenting that occurred during the 1980s has been examined along a variety of dimensions. Ours is the first study to our knowledge that has sought to determine whether the increasing trend towards formal intellectual property protection has restricted the breadth of knowledge flows. Our findings suggest that it has.

[46]In Period 2, the difference in university-firm fragmentation is 0.027-0.019=0.008 and the firm sample mean is 0.867.

[47]In Period 2, the difference in university-firm fragmentation is 0.020-0.014=0.006 and the firm sample mean is 0.908.

However, although the magnitude of the increase in concentration of university knowledge flows is large relative to firms, the absolute changes are modest. Also important is that the changes are at least partly driven by universities that were experienced at patenting, suggesting that the identified effect is likely not temporary.

What are the broader implications of these findings? There could be many explanations and we are cautious about pushing too hard on any one interpretation of our results. However, we close by drawing on the literature to speculate about some potential causes to offer context for our findings.

In terms of knowledge outflows, our results suggest that not only might behaviors associated with patenting limit the level of dissemination of knowledge flows as shown by Murray and Stern (2005), these behaviors might also limit the breadth of dissemination. In the university setting, this could occur at either or both of two levels: the technology licensing office and/or the inventor.

To the extent technology licensing offices shift their objective function from dissemination-maximization (leading to predominantly non-exclusive, widely licensed patents) to profit-maximization (leading to predominantly narrowly licensed patents), we would observe a decrease in forward fragmentation, consistent with our findings. It seems plausible that such a shift could occur given that performance metrics for the latter are much easier to measure.

One could also imagine how plausible changes in inventor behavior could result in the findings reported here. Due to the early stage nature of most university inventions, the transfer of tacit knowledge is particularly important for commercial development (likely leading to the creation of follow-on inventions that also will be patented and may cite the original patent). Such tacit knowledge is often most efficiently transferred through direct interaction with the inventor (Jensen and Thursby (2001); Agrawal (2006)). To the extent that inventors become more commercially oriented regarding the management of their intellectual property, and the findings of Lach and Schankerman (2005) suggest this is not unlikely, their tendency to share tacit knowledge with others who are not licensees may diminish.

Alternatively, a shift in inventor research behavior, rather than dissemination behavior, could also generate our findings. To the extent that faculty change the nature of their research such that the resultant inventions are only applicable to a more narrow range of subsequent users, this could explain our findings. However, it is important to recall that we employ technology field fixed effects such that our results are not driven by changes from, say, chemistry to biotechnology where the set of potential knowledge users might be more concentrated. Furthermore, we control for generality such that our results are not driven by a change in research projects towards less general inventions that are therefore applicable to a smaller set of firms. Thus, only a particular type of change in research behavior, that results in inventions that are within the same field and equally general but for other reasons are only applicable to a more concentrated set of users, would cause the phenomenon we identify.

In terms of knowledge inflows, our results suggest that the breadth of assignees that inventors draw upon in developing their own inventions diminished over time. Although it is difficult to imagine how this could be a direct result of changes in behavior by technology licensing offices, an explanation based on changes in inventor behavior is reasonably straightforward. If inventors become more commercially oriented and savvy over time, they may increasingly look forward and anticipate that, to the extent that future licensees are exposed to anti-commons problems associated with access to complementary inventions, the value of their inventions will be diminished. As such, inventors reason back and plan their research program in a manner that minimizes anti-commons exposure by reducing the breadth of prior art citations. This seems reasonable given that university researchers have been shown to respond to economic incentives (Lach and Schankerman (2005)).

It is important to note that although it is tempting to assume that higher concentrations of knowledge inflows and particularly outflows are welfare reducing, this is not necessarily true. Knowing that knowledge spillovers contribute to economic growth (Romer (1986); Romer (1990)) but also recognizing the importance of exclusivity for creating incentives to develop and commercialize, it is unclear how increased concentration of university knowledge flows affects welfare. What is clear, however, is that what we learn from further study of this topic will offer important insight for science policy and economic growth.

References

Agrawal, Ajay, "Engaging the Inventor: Exploring Licensing Strategies for University Inventions and the Role of Latent Knowledge," *Strategic Management Journal*, January 2006, *27* (1), 63–79.

_ **and Lorenzo Garlappi**, "Public Sector Science and the Strategy of the Commons," *Economics of Innovation and New Technology*, 2007, *forthcoming.*

_ **and Rebecca Henderson**, "Putting Patents in Context: Exploring Knowledge Transfer from MIT," *Management Science*, January 2002, *48* (1), 44–60.

Ai, Chunrong and Edward Norton, "Interaction Terms in Logit and Probit Models," *Economic Letters*, July 2003, *80* (1), 123–29.

Argyres, Nicholas and Julia Liebskind, "Privatizing the Intellectual Commons: Universities and the Commercialization of Biotechnology Research," *Journal of Economic Behavior and Organization*, May 1998, *35* (4), 427–54.

Breschi, Stefano, Francesco Lissoni, and Fabio Montobbio, "The Scientific Productivity of Academic Inventors: New Evidence From Italian Data," May 2005. CESPRI Working Paper No. 168.

Buenstorf, G., "Commercializing Basic Science as a Competitor or Complement of Academic Accomplishment? The Case of Max Planck Directors," 2005. mimeo, Max Planck Institute of Economics.

Calerini, Mario and Chiara Franzoni, "Is Academic Patenting Detrimental to High Quality Research? An Empirical Analysis of the Relationship Between Scientific Careers and Patent Applications," 2004. CESPRI Working Paper No. 162.

Carayol, Nicolas, "Academic Incentives, Research Organization, and Patenting at a Large French University," 2005. mimeo, Universite Louis Pasteur.

Cockburn, Iain, Sam Kortum, and Scott Stern, "Are All Patent Examiners Equal? The Impact of Examiner Characteristics on Patent Statistics and Litigation Outcomes," 2002. National Bureau of Economic Research, Working Paper 8980.

Cohen, Wesley, Richard Florida, Lucien Randazzese, and John Walsh, "Industry and the Academy: Uneasy Partners in the Cause of Technological Advance," in Roger Noll, ed., *Challenges to the Research University*, Brookings Institution, 1998, pp. 171–200.

Colyvas, Jeannette, Michael Crow, Annetine Gelijns, Roberto Mazzoleni, Richard Nelson, Nathan Rosenberg, and Bhaven Sampat, "How Do University Inventions Get Into Practice?," *Management Science*, January 2002, *48* (1), 61–72.

David, Paul, "Will Building Good Fences Really Make Good Neighbors in Science?," 2001. Stanford Working Paper: 01-005.

_ , "Can 'Open Science' be Protected from the Evolving Regime of IPR Protections?," 2003. Stanford Working Paper: 03-011.

Easterly, William and Ross Levine, "Africa's Growth Tragedy: Policies and Ethnic Division," *Quarterly Journal of Economics*, November 1997, *112* (4), 1203–50.

Eisenberg, Rebecca, "Patent Swords and Shields," *Science*, February 2003, *299* (5609), 1018.

Etzkowitz, Henry, "The Norms of Entrepreneurial Science: Cognitive Effects of the New University-Industry Linkages," *Research Policy*, December 1998, *27* (8).

Goldfarb, Brent, Gerald Marshke, and Amy Smith, "Scholarship and Inventive Activity in the University: Complements or Substitutes?," 2006. mimeo, University of Maryland.

Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg, "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools," in Adam Jaffe and Manuel Trajtenberg, eds., *Patents, Citations, & Innovations: A Window on the Knowledge Economy*, The MIT Press, 2002, pp. 403–59.

_ **and Rosemarie Ham Ziedonis**, "The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semicondocutor Industry, 1979-1995," *The Rand Journal of Economics*, Spring 2001, *32* (1), 101–28.

Heller, Michael and Rebecca Eisenberg, "Can Patents Deter Innovation? The Anticommons in Biomedical Research," *Science*, May 1998, *280* (5364), 698–701.

Henderson, Rebecca, Adam Jaffe, and Manuel Trajtenberg, "Universities as a Source of Commercial Technology: A Detailed Analysis of University Patenting, 1965-1988," *The Review of Economics and Statistics*, February 1998, *80* (1), 119–27.

Information Products Division, Technology Assessment and Forecast Branch, "U.S. Colleges and Universities - Utility Patent Grants, Calendar Years 1969-2000," Technical Report, U.S. Patent and Trademark Office 2002. http://www.uspto.gov/web/offices/ac/ido/oeip/taf/univ/univtoc.htm.

Jaffe, Adam and Josh Lerner, *Innovation and Its Discontents: How Our Broken Patent System is Endangering Innovation and Progress, and What to Do About It*, Princeton University Press, 2004.

_ **, Manuel Trajtenberg, and Michael Fogarty**, "The Meaning of Patent Citations: Report on the NBER/Case Western Reserve Survey of Patentees," in Adam Jaffe and Manuel Trajtenberg, eds., *Patents, Citations, & Innovations: A Window on the Knowledge Economy*, The MIT Press, 2002, pp. 379–402.

Jensen, Richard and Marie Thursby, "Proofs and Prototypes for Sale: The Licensing of University Inventions," *American Economic Review*, March 2001, *91* (1), 240–59.

Kortum, Samuel and Jonathan Putnam, "Assigning Patents to Industries: Tests of the Yale Technology Concordance," *Economic Systems Research*, June 1997, *9* (2), 161–175.

Krimsky, Sheldon, *Science and the Private Interest*, Rowman-Littlefield Publishing Co., 2003.

Lach, Saul and Mark Schankerman, "Incentives and Invention in Universities," July 2005. NBER Working Paper 9727.

Lessig, L, *The Future of Ideas: The Fate of the Commons in a Connected World*, Random House, 2002.

Lieberwitz, Risa, "Confronting the Privatization and the Commercialization of Academic Research: An Analysis of Social Implications at the Local, National, and Global Levels," *Indiana Journal of Global Legal Studies*, Winter 2005, *12* (1), 109–52.

Markiewicz, Kira and Alberto DiMinin, "Commercializing the Laboratory: The Relationship Between Faculty Patenting and Publishing," 2005. mimeo, UC Berkeley.

Mazzoleni, Roberto, "University Patents, R&D Competition, and Social Welfare," *Economics of Innovation and New Technology*, September 2005, *14* (6), 499–515.

Mowery, David, Richard Nelson, Bhaven Sampat, and Arvdis Ziedonis, *Ivory Tower and Industrial Innovation, University-Industry Technology Transfer Before and After the Bayh-Dole Act in the United States*, Stanford Business Books, 2004.

Murray, Fiona and Scott Stern, "Do Formal Intellectual Property Rights Hinder the Free Flow of Scientific Knowledge? An Empirical Test of the Anti-Commons Hypothesis," 2005. National Bureau of Economic Research, Working Paper 11465.

National Institute of Health, "Best Practices for the Licensing of Genomic Inventions," Technical Report, National Institute of Health 2005. Federal Register.

National Science Board, "Science and Engineering Indicators 2004," Technical Report, National Science Board 2004. Appendix, Table 4.8, http://www.nsf.gov/statistics/seind04.

Nelson, Richard, *National Innovation Systems: A Comparative Analysis*, Oxford University Press, 1993.

_ , *The Sources of Economic Growth*, Harvard University Press, 1996.

Papke, Leslie and Jeffrey Wooldridge, "Econometric Methods for Fractional Response Variables with an Application to 401 (K) Plan Participation Rates," *Journal of Applied Econometrics*, November-December 1996, *11* (6), 619–32.

Rivette, Kevin and David Kline, *Rembrandts in the Attic: Unlocking the Hidden Value of Patents*, Harvard Business School Press, 2000.

Romer, Paul, "Increasing Returns and Long-Run Growth," *Journal of Political Economy*, October 1986, *94* (5), 1002–37.

_ , "Endogenous Technological Change," *Journal of Political Economy*, October 1990, *98* (5).

Serrano, Carlos J., "The Market for Intellectual Property: Evidence from the Transfer of Patents," 2005. working paper, University of Toronto.

Shapiro, Carl, "Navigating the Patent Thicket: Cross Licenses, Patent Pools and Standard Setting," *Innovation Policy and the Economy*, 2001, *1*, 119–50.

Stokes, Donald E., *Pasteur's Quadrant: Basic Science and Technological Innovation*, Brookings Institution Press, 1997.

Trajtenberg, Manuel, Rebecca Henderson, and Adam Jaffe, "University Versus Corporate Patents: A Window on the Basicness of Invention," *Economics of Innovation and New Technology*, May 1997, *5* (1), 19–50.

VanLooy, B., J. Callaert, and K. Debackere, "Publication and Patent Behavior of Academic Researchers: Conflicting, Reinforcing, or Merely Co-existing?," 2005. mimeo, K.U. Leuven, Belgium.

Walsh, John, Charlene Cho, and Wesley Cohen, "View From the Bench: Patents and Material Transfer," *Science*, September 2005, *309*, 2002–3.

Warshofsky, Fred, *The Patent Wars: The Battle to Own the World's Technology*, John Wiley & Sons, Inc., 1994.

Ziedonis, Rosemarie Ham, "Don't Fence Me In: Fragmented Markets for Technology and the Patent Acquisition Strategies of Firms," *Management Science*, June 2004, *50* (6), 804–20.

Table 1: Summary Statistics, Means, Standard Deviations and Difference in Means

Panel A: Knowledge OUTFLOWS

	Period 1: 1980-1983			Period 2: 1986-1989		
	University (I)	Firm (II)	Difference (I) - (II)	University (III)	Firm (IV)	Difference (III) - (IV)
Forward Fragmentation	0.902	0.879	0.023	0.861	0.867	-0.006
	(0.187)	(0.223)		(0.214)	(0.216)	
Generality	0.571	0.538	0.033	0.561	0.547	0.013
	(0.332)	(0.361)		(0.316)	(0.338)	
Citations Received	8.62	6.37	2.25	11.65	8.85	2.800
	(10.03)	(5.94)		(13.28)	(10.31)	
University Citation Intensity	0.065	0.013	0.052	0.101	0.018	0.083
	(0.136)	(0.068)		(0.178)	(0.078)	
Observations	1,125	70,699		2,705	98,970	

Panel B: Knowledge INFLOWS

	Period 1: 1980-1983			Period 2: 1990-1993		
	University (I)	Firm (II)	Difference (I) - (II)	University (III)	Firm (IV)	Difference (III) - (IV)
Backward Fragmentation	0.918	0.903	0.015	0.905	0.908	-0.002
	(0.200)	(0.220)		(0.211)	(0.197)	
Originality	0.535	0.514	0.021	0.563	0.515	0.048
	(0.374)	(0.388)		(0.355)	(0.364)	
Citations Made	5.374	4.608	0.766	6.493	6.458	0.035
	(4.767)	(3.574)		(5.726)	(6.383)	
University Citation Intensity	0.050	0.007	0.042	0.090	0.017	0.073
	(0.139)	(0.053)		(0.178)	(0.076)	
Observations	1,212	72,050		4,437	123,734	

Notes: Standard deviations in parenthesis.

Table 2: Forward Fragmentation, OLS and Fractional Logit Regression Marginal Effects

	Panel A: OLS Regressions Dependent Variable: *ForFrag*				Panel B: Fractional Logit Regression Dependent Variable: *ForFrag*			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
University Dummy	0.037^{***}	0.036^{***}	0.032^{***}	0.031^{***}	0.032^{***}	0.031^{***}	0.028^{***}	0.027^{***}
	5.624	5.444	5.025	4.874	6.636	6.431	5.700	5.575
University Dummy x Era Dummy	-0.026^{***}	-0.025^{***}	-0.024^{***}	-0.023^{***}	-0.022^{***}	-0.021^{***}	-0.020^{***}	-0.019^{***}
	-3.328	-3.197	-3.066	-2.940	-3.618	-3.475	-3.279	-3.160
Citations Received		0.001^{***}		0.001^{***}		0.001		0.000
		4.850		4.106		1.185		0.698
Citations Received x Era Dummy		-0.001^{***}		-0.000^{***}		-0.001		-0.001
		-3.793		-3.712		-1.029		-0.847
Generality			0.090^{***}	0.090^{***}			0.081^{***}	0.080^{***}
			40.33	40.24			34.06	34.19
Generality x Era Dummy			0.008^{***}	0.009^{***}			0.012^{***}	0.013^{***}
			2.828	2.889			3.745	4.101
University Intensity	0.017	0.016	0.001	0.000	0.013	0.013	-0.003	-0.003
	1.448	1.389	0.068	0.021	0.810	0.785	-0.175	-0.189
University Intensity x Era Dummy	0.009	0.009	0.010	0.011	0.009	0.010	0.010	0.011
	0.615	0.661	0.727	0.765	0.499	0.484	0.547	0.561
Tech. Field F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Tech. Field F.E. x Era Dummy	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.042	0.042	0.064	0.064				
Log Likelihood					$-54,028$	$-54,022$	$-53,225$	$-53,223$
Observations	173,499	173,499	173,499	173,499	173,499	173,499	173,499	173,499

- Fractional logit regression results are the marginal effects evaluated at the sample mean.
- *** 1% significance, ** 5% significance, * 10% significance
- Robust t-statistics shown.

Table 3: Forward Fragmentation Based on University Experience

	Panel A: OLS Regressions Dependent Variable: *ForFrag*				Panel B: Fractional Logit Regression Dependent Variable: *ForFrag*			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
High Experience University Dummy	0.037***	0.036***	0.033***	0.032***	0.032***	0.031***	0.028***	0.027***
	5.350	5.168	4.757	4.604	6.331	6.119	5.428	5.301
High Experience University Dummy	-0.021**	-0.020**	-0.018**	-0.017**	-0.018***	-0.017**	-0.015**	-0.014**
x ERA Dummy	-2.485	-2.354	-2.170	-2.046	-2.649	-2.504	-2.292	-2.179
Low Experience University Dummy	0.033*	0.033*	0.030*	0.030*	0.029**	0.029**	0.026*	0.025*
	1.828	1.801	1.696	1.673	2.158	2.131	1.883	1.863
Low Experience University Dummy	-0.036*	-0.035*	-0.036*	-0.036*	-0.032**	-0.031**	-0.031**	-0.030*
x ERA Dummy	-1.811	-1.795	-1.841	-1.820	-2.039	-2.026	-1.989	-1.960
Citations Received		0.001***		0.001***		0.001		0.000
		4.849		4.105		1.183		0.697
Citations Received		-0.001***		-0.001***		-0.001		-0.001
x ERA Dummy		-3.789		-3.709		-1.027		-0.845
Generality			0.090***	0.090***			0.081***	0.080***
			-40.33	40.24			34.06	34.19
Generality			0.009***	0.009***			0.012***	0.013***
x ERA Dummy			2.833	2.894			3.743	4.098
University Intensity	0.017	0.016	0.001	0.000	0.013	0.013	-0.003	-0.003
	1.448	1.389	0.068	0.021	0.810	0.785	-0.175	-0.189
University Intensity	0.009	0.009	0.010	0.011	0.009	0.010	0.010	0.010
x ERA Dummy	0.601	0.647	0.711	0.750	0.438	0.474	0.537	0.550
Tech. Field F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Tech. Field F.E. x ERA Dummy	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.042	0.042	0.064	0.064				
Loglikelihood					-54,028	-54,021	-53,224	-53,222
Observations	173,499	173,499	173,499	173,499	173,499	173,499	173,499	173,499

- Fractional logit regression results are the marginal effects evaluated at the sample mean.
- *** 1% significance, ** 5% significance, * 10% significance
- Robust t-statistics shown.

Table 4: Backward Fragmentation, OLS and Fractional Logit Regression Marginal Effects

	Panel A: OLS Regressions Dependent Variable: *BackFrag*				Panel B: Fractional Logit Regression Dependent Variable: *BackFrag*			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
University Dummy	0.026^{***}	0.026^{***}	0.025^{***}	0.024^{***}	0.023^{***}	0.022^{***}	0.021^{***}	0.020^{***}
	4.414	4.291	4.213	4.131	4.686	4.534	4.429	4.364
University Dummy x Era Dummy	-0.015^{**}	-0.014^{**}	-0.017^{**}	-0.016^{**}	-0.013^{**}	-0.012^{**}	-0.014^{**}	-0.014^{***}
	-2.252	-2.140	-2.528	-2.448	-2.284	-2.136	-2.553	-2.477
Citations Made		0.001^{***}		0.001^{***}		0.001^{*}		0.001
		5.267		3.531		1.709		0.811
Citations Made x Era Dummy		-0.000		-0.000		0.000		0.000
		-0.301		-0.154		0.245		0.255
Originality			0.066^{***}	0.066^{***}			0.060^{***}	0.059^{***}
			34.05	33.83			28.60	28.49
Originality x Era Dummy			0.011^{***}	0.011^{***}			0.012^{***}	0.011^{***}
			4.481	4.236			4.428	4.330
University Intensity	0.006	0.006	0.004	0.004	0.004	0.004	0.004	0.004
	0.452	0.456	0.265	0.269	0.218	0.235	0.218	0.227
University Intensity x Era Dummy	0.016	0.017	0.013	0.013	0.015	0.015	0.009	0.010
	1.056	1.080	0.868	0.887	0.673	0.690	0.450	0.467
Tech. Field F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Tech. Field F.E. x Era Dummy	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.028	0.029	0.045	0.046				
Log Likelihood					$-53,095$	$-53,050$	$-52,248$	$-52,234$
Observations	201,433	201,433	201,433	201,433	201,433	201,433	201,433	201,433

- Fractional logit regression results are the marginal effects evaluated at the sample mean.
- *** 1% significance, ** 5% significance, * 10% significance
- Robust t-statistics shown.

Table 5: Backward Fragmentation Based on University Experience

	Panel A: OLS Regressions Dependent Variable: *BackFrag*				Panel B: Fractional Logit Regression Dependent Variable: *BackFrag*			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
High Experience University Dummy	0.025***	0.025***	0.024***	0.024***	0.022***	0.021***	0.020***	0.020***
	3.861	3.764	3.682	3.617	4.023	3.901	3.758	3.706
High Experience University Dummy x ERA Dummy	-0.017**	-0.016**	-0.019**	-0.018**	-0.014**	-0.013**	-0.015**	-0.015**
	-2.164	-2.061	-2.430	-2.356	-2.127	-1.993	-2.332	-2.261
Low Experience University Dummy	0.030**	0.029**	0.028**	0.028**	0.026**	0.024**	0.024**	0.024**
	2.228	2.145	2.133	2.078	2.573	2.464	2.545	2.495
Low Experience University Dummy x ERA Dummy	-0.017	-0.014	-0.017	-0.016	-0.013	-0.012	-0.015	-0.014
	-1.008	-0.998	-1.169	-1.124	-1.194	-1.105	-1.403	-1.359
Citations Made		0.001***		0.001***		0.001*		0.001
		5.264		3.529		1.702		0.808
Citations Made x ERA Dummy		-0.000		-0.000		0.000		0.000
		-0.301		-0.154		0.245		0.254
Originality			0.066***	0.066***			0.060***	0.059***
			34.05	33.83			28.59	28.48
Originality x ERA Dummy			0.011***	0.011***			0.012***	0.011***
			4.482	4.237			4.435	4.337
University Intensity	0.006	0.006	0.003	0.004	0.004	0.004	0.004	0.004
	0.446	0.450	0.259	0.263	0.214	0.231	0.214	0.223
University Intensity x ERA Dummy	0.016	0.017	0.013	0.014	0.015	0.015	0.009	0.010
	1.059	1.082	0.870	0.890	0.675	0.691	0.451	0.469
Tech. Field F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Tech. Field F.E. x ERA Dummy	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.028	0.029	0.045	0.046				
Loglikelihood					-53,095	-53,049	-52,248	-52,234
Observations	201,433	201,433	201,433	201,433	201,433	201,433	201,433	201,433

- Fractional logit regression results are the marginal effects evaluated at the sample mean.
- *** 1% significance, ** 5% significance, * 10% significance
- Robust t-statistics shown.

Table 6: Change in Propensity of University Patents to have Perfectly Concentrated Knowledge Flows

	Backward Knowledge Flows				Forward Knowledge Flows			
	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)
Period 1 Average	0.921	0.920	0.926	0.925	0.910	0.912	0.911	0.913
Period 2 Average	0.914	0.914	0.916	0.916	0.869	0.869	0.874	0.874
$\frac{Y}{T}$	0.007	0.007	0.011	0.010	0.045	0.047	0.041	0.043

-*Note*: The Roman numerals in the table coincide with the specifications of our regression equations reported above (i.e. in terms of the use of originality and citations made for the knowledge inflows case and generality and citations received for the outflows case.).