Capturing Knowledge: The Location Decision of New PhDs Working in Industry

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Abstract

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The placement of new PhDs with firms provides a means by which knowledge is transferred from the university. This means of knowledge transfer is especially important in facilitating the movement of tacit knowledge. Despite the role that new PhDs play in this university-industry interface, we know very little about industrial placements. One dimension of ignorance involves the extent to which students stay in close geographic proximity to where they received training. This paper examines factors that influence the probability that a newly-trained PhD will remain "local" or stay in-state. Specifically, we measure how various individual, institutional and geographic attributes affect the probability that new PhDs who choose to work in industry stay in the metropolitan area or state where they were trained.

Our study focuses on PhDs who received their degree in one of ten fields of science and engineering during the period 1997-1999. Data for the study come from the Survey of Earned Doctorates, administered by Science Resources Statistics, National Science Foundation. We find that state and local areas capture knowledge embodied in newly minted PhDs headed to industry, but not at an overwhelming rate. Certain states and metropolitan areas have an especially high attrition rate. We also find that in certain instances attrition is higher from top-rated PhD programs than from lower-rated programs and higher for those supported on fellowships, suggesting that local areas are less able to retain the best. Our results also suggest that retention is related to personal characteristics such as level of debt, previous work experience and visa status. Retention is also related to the local technological infrastructure.

Section I. Introduction

The placement of newly-minted science and engineering PhDs provides one means by which knowledge is transferred from the university to industry. The placement of PhDs with industry can be especially important in facilitating the movement of tacit knowledge. Despite this role, we know very little about industrial placements. One dimension of ignorance involves the extent to which students stay where trained or leave the area/state after receiving the degree. The policy relevance of this question is obvious. Creating a highly skilled work force is one of several ways universities contribute to economic growth (Stephan et al. 2004). The mobility of the highly educated affects the extent to which knowledge created in universities is absorbed by the local economy.[1] Having graduates work for neighboring firms strengthens the interface between the university and firms at the local or state level, and makes it easier for future graduates to find jobs with employers near the university. Moreover, the availability of a highly-trained work force attracts new businesses to the local area.

To the extent that students "fly the coop," one rationale for investing state and local resources in universities is weakened. This is especially the case in today's environment when universities, in an effort to attract resources, herald the role they play in local economic development, mindful of Stanford's role in the creation of Silicon

[1]PhDs working in industry clearly contribute more than knowledge transfer. Stern (1999) discusses industrial scientists' interest in" Science" which, to continue Stern's typology, leads to "Productivity" for the firm. The ability to engage in" Science" provides psychic rewards for the scientist. The productivity effects experienced by the firm result in part from the "ticket of admission" that the practice of "Science" provides the firm to the wider scientific community (Stern 1999, p. 11). We focus on the knowledge-transfer role here because of our interest in the interface between industry and academe and the geographical dimensions of this interface.

Valley, M.I.T. and Harvard's role in Route 128, and Duke and the University of North Carolina's role in the Research Triangle Park (Link, 1995).[2]

The migration behavior of the highly educated thus not only has long-term implications for the economic health of a region, but also may affect the amount policymakers are willing to invest in higher education. The stakes are somewhat different for private institutions than for public institutions. Not beholden to the public sector for funding, it is less essential that private institutions demonstrate a local economic impact. Nonetheless, private institutions receive a number of benefits from the state and local area, not the least of which is tax-exempt status.

This is not to say that universities are solely focused on keeping their graduates close at hand. Placements outside the local area are an indication of success, signaling that the university has the necessary connections and reputation to warrant more distant placements.[3] Moreover, strong industrial placements, regardless of whether or not they are local, can enhance future funding opportunities with industry. They can also enrich the alumni base and thus potential donations to the university.

The objective of this paper is to examine factors that influence the probability that a highly skilled worker will remain 'local' or stay in the state. Specifically, we measure how various individual, institutional, and geographic attributes affect the probability that new PhDs going to industry stay in the metropolitan area or state where they trained. Our study focuses on PhDs who received their degree in one of ten fields in science and

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[2] There is a culture in universities of expecting PhDs going into academe to seek the best available positions, regardless of locale. Attitudes towards industrial placements are less clear-cut. Stephan and Black (1999) find that in the field of bioinformatics often faculty don't even know the name of the firms their students go to work for.

[3] Mansfield's work (1995) suggests that industry, when looking for academic consultants, is likely to use local talent for applied research, but focuses on getting the "best" regardless of distance when basic research is involved.

engineering (S&E) during the period 1997-1999. Data come from the Survey of Earned Doctorates, administered by Science Resources Statistics National Science Foundation.

The paper proceeds as follows. Section II provides a discussion of the role new PhDs play in knowledge transfer. Section III briefly discusses the role of geographic proximity in promoting knowledge transfer. Section IV offers a conceptual model of the individual decision to migrate. Section V discusses the data used for this study and provides some descriptive statistics on the migration of industrial PhDs from metropolitan areas and states, focusing on the ability of MSAs and states to retain PhDs produced in their region and/or import human capital from other regions. Section VI gives the results from our empirical analyses and discusses the policy implications. Section VII concludes by summarizing and discussing the key findings.

Section II: The Role of New PhDs in Knowledge Transfer

The transmission mechanism by which knowledge flows from universities to firms is varied, involving formal means, such as publications, as well as less formal mechanisms, such as discussions between faculty and industrial scientists at professional meetings. Graduate students are one component of the formal means by which knowledge is transferred. Much of graduate students' training is of a tacit nature, acquired while working in their mentor's lab. These new techniques, which cannot be codified, can be transmitted to industrial R&D labs through the hiring of recently-trained scientists and engineers. New hires also establish and reinforce existing networks between firms and university faculty whereby the firm can acquire more ready access to new knowledge being created in the university. [4]

The Carnegie Mellon Survey of R&D labs in manufacturing located in the U.S. asked respondents to rank the importance of ten possible sources of information concerning public knowledge for a recently completed "major" R&D project (Cohen, Nelson and Walsh, 2002). A four-point Likert scale was used. The ten sources included patents, publications/reports, meetings or conferences, informal interaction, recently-hired graduates, licenses, cooperative/JVs, contract research, consulting and personal exchange. The findings show that--across all industries--publications/reports are the dominant means by which R&D facilities obtain knowledge from the public sector. Next in importance are informal information exchange, public meetings or conferences, and consulting. Recently-hired graduates show up in the second cluster, which, in the overall rankings, is lower than the first cluster of sources of public knowledge. In certain industries, however, 30% or more of the respondents to the Carnegie Mellon Survey indicate that recently hired graduates played at least a "moderately important" role in knowledge transfer. These industries are: drugs, mineral products, glass, concrete, cement, lime, computers, semiconductors and related equipment and TV/radio. This finding likely relates to the relative importance of tacit knowledge in certain fields and the key role that graduate students play in the transmission of tacit knowledge.[5]

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[4] Networks have been found to relate to firm performance (Powell, Koput, Smith-Doerr, and Owen-Smith 1998; Zucker and Darby 1997).

[5] The second tier ranking of graduates as a means of knowledge transfer reflects in part the fact that graduate students contribute indirectly through networking to several pathways of knowledge transfer (such as informal information exchange, public meetings or conferences, and consulting) that are listed separately on the questionnaire.

In a related study, Agrawal and Henderson (2002) interviewed 68 engineering faculty at MIT, all of whom had patented and licensed at least one invention, asking them to "estimate the portion of the influence your research has had on industry activities, including research, development, and production" that was transmitted through a number of channels. Consulting headed the list, with a weight of 25.1%, followed by publication at 18.5%. Placement of MIT graduates was a close third at 16.8%.

III: The Role of Geographic Proximity in Transmitting Knowledge

Considerable research has focused on the role that geographic proximity plays in transmitting knowledge. Early work by Jaffe (1989), for example, used university research and development expenditures as a proxy for the availability of local knowledge spillovers as did work by Audretsch and Feldman (1996a, 1996b). More recent work by Feldman and Audretsch (1999), Anselin, Varga and Acs (1997, 2000) and Black (2001) has followed suit, shifting the analysis from the state to the CMSA. In each study a significant relationship is found between the dependent variable, which is a measure of innovation, and the proxy measure for local knowledge. Zucker, Darby and Brewer (1998) take a different path and examine the role that the presence of star scientists in a region play in determining the regional distribution of biotech-using firms. They find the number of active stars in the region to play an important role in determining firm activity. Moreover, the effect is in addition to the role played by general knowledge sources, as measured by a "top quality university" or number of faculty with federal support.

Two recent studies use patent citations to examine the degree to which knowledge spillovers are geographically bounded. Thompson (2005) finds that inventor citations in the United States are 25 percent more likely to match the state or metropolitan area of their citing patent than are examiner citations. Almeida and Kogut (1999) explore why patent citations are more regionally concentrated in certain areas than others, focusing on the semiconductor industry. They argue that the mobility of engineers plays a key role in explaining citation rates by region. Regions that have high inter-firm mobility of inventors (as measured by inventor address) have higher rates of intra-regional citation than regions with low inter-firm migration. This suggests that "a driving force for local externalities in semiconductor design is the mobility of people." (p. 906).

These, and countless other studies, go a long way toward establishing that geographic proximity promotes the transmission of knowledge. *They do not, however, address the extent to which knowledge spillovers are local.* One of the few papers to examine this question was written by Audretsch and Stephan (1996) and examines academic scientists affiliated with biotech companies. Because the authors know the location of both the scientist and the firm, they are able to establish the geographic origins of spillovers embodied in this knowledge-transfer process. Their research shows that although proximity matters in establishing formal ties between university-based scientists and companies, its influence is anything but overwhelming. Approximately 70% of the links between biotech companies and university-based scientists in their study were non-local. Audretsch and Stephan also estimate the probability that the link is local.

Here we extend the Audretsch-Stephan framework, examining the location decisions of recent graduates. We are particularly interested in knowing the degree to which available knowledge spillovers, as measured by the placement of PhD students, are local and in knowing factors related to the "stickiness" of PhD-embodied knowledge to the local area.

Section IV: Determinants of Migration

There is a vast literature examining factors that influence human migration, much of which owes its origin to the work of Sjaastad (1962), and which views migration as an investment decision. An individual will move if s/he perceives the present value of the stream of benefits resulting from the move, composed primarily of gains in real income, to be greater than the costs, composed of both pecuniary and psychic costs to moving.

Here we are interested in modeling the decision of a PhD headed to industry to locate outside the city (state) of training versus to stay in the city (state) of training. We assume that the new PhD is interested in maximizing the present value of utility over the life cycle, where the utility function has arguments of both income and psychic attributes such as family well being. The cost of moving involves psychic costs as well as monetary costs of relocation (some of which may be paid by the firm). We assume that the individual engages in search in an extensive way while in graduate school and thus does not forego actual income while looking for a job. Moreover, we assume that capital markets are not perfect and thus individuals with little debt are more able to absorb the costs of moving than those with debt. We also assume that individuals with access to a wider network of information are more likely to move than are those with more limited access.

Our model focuses on *whether* the PhD leaves where s/he is trained. Three sets of explanatory variables are of interest: Variables that reflect attributes of the state and local area, variables that reflect individual characteristics affecting the present value of the discounted stream of utility from moving compared to the present value of the discounted stream of utility from staying in the area, and variables that reflect field of training and institutional characteristics.   From a policy perspective, we are also interested in knowing whether individuals trained at a private institution are more likely to leave than are individuals trained at a public institution. We are also interested in knowing whether in-state students, as measured by receiving one's high school, college and PhD degrees in the same state, are more likely to stay.

Attributes of the local area include the degree of innovative activity, job market prospects in industry for PhDs and the desirability of the location. Innovative activity is measured by such standard measures as patent counts, R&D expenditures, etc.; desirability is measured by level of education and per capita income. Job market prospects for PhDs in industry are measured by an index, explained below, that computes the employment absorptive capacity of the area. Personal characteristics affecting the net present value include age, marital status, and the presence of dependents.

Variables that reflect wider access to networks include the rank of the department as well as whether or not the individual was supported on a fellowship during graduate school. We expect individuals who work full or part time during their last year in graduate school to be more connected to the local area and therefore more likely to stay. We also expect individuals who return to a job they held before coming to graduate school to be more likely to remain in the area. The assumption is that proximity plays a role in selecting the graduate program.

Imperfect capital markets lead us to expect that individuals who leave graduate school with substantial debt face more constrained searches and thus are more likely to remain local. Preferences are also assumed to affect the decision to relocate. While difficult to measure, we make inferences concerning preferences based on the individual's past pattern of mobility.

Section V: S&E PhDs in Industry: Where They Come from and Where They Go

Data for this paper come from the Survey of Earned Doctorates (SED) administered by Science Resources Statistics (SRS) of the National Science Foundation (NSF). The survey is given to all doctorate recipients in the U.S., and has a response rate of approximately 92%. While the SED has always asked graduates whether they have definite plans to work with a firm, the identity and geographic location of the firm has only become available to researchers since 1997 and then only in verbatim form. We have recently used these verbatim files to code the identity of the firm for the period 1997-1999.

The analysis is thus restricted to PhDs in science and engineering who made a definite commitment to an employer in industry between 1997 and 1999. This undercounts PhD placements in industry in two notable ways. First, many PhDs who eventually end up working in industry initially take postdoctoral appointments, particularly PhDs in the life sciences. Secondly, 37.1% of PhDs who were immediately planning to work in industry did not list a specific firm or location because they had not made a definite commitment to an employer at the time the survey was administered.[6] Our results are thus conditional on the acceptance of a position with industry at the time the survey was completed and do not apply to all PhDs headed to industry.

[6] 17,382 of the 75,243 PhDs awarded in the 12 broad S&E fields during this time period had plans to work in industry. Of these, 10,932 (14.5 % of all PhDs in S&E during this time period) had made a definite commitment to an employer in industry and identified the specific name of the firm they planned to work for. Of these, 10,121 PhDs were awarded by institutions in the continental U.S. in one of ten "exact" S&E fields.

The fields of training of the 10,121 new PhDs with definite plans to work in industry are given in Table 1. Not surprisingly, the data is dominated by large fields having a tradition of working in industry as well as a tradition of not accepting a post doc position prior to heading to industry. Fifty-three percent of the sample is made up of engineers; 12% of chemists.

For PhDs who had made a definite commitment to an employer in industry and identified the specific name of the firm they plan to work for between 1997 and 1999, 36.7 % had commitments with an employer that lay within the same state as their doctoral institution.[7]

The stay rate is low compared to that for bachelor and master degree recipients in science and engineering. The National Science Foundation reports that 62% of all recent bachelors in science and engineering in the United States stay in the state where they received their degree and 60.2% of all recent masters stay. The stay rate is highest for computer scientists (68.4% for bachelors and 70.8% for masters) and lowest for bachelors in engineering (55.1%) and masters in the physical sciences (54.1%).[8] The PhD stay-rate of 36.7% is also low compared to recent law school graduates for whom 57.0% with known employment status remain in the state of training (National Association for Law Placement, 1998).

The low stay-within-state rate does not necessarily indicate that the production of new PhDs is a poor investment from state policymakers' perspectives. In all but five states, institutions within the state represent the top suppliers of new PhDs hired by firms

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[7] The percent is based on the 10,932 referred to in footnote 6 which includes PhDs trained in psychology and economics, as well as the ten fields listed in Table 1.
[8] The data are not strictly comparable since the NSF data include U.S. degree recipients who also received a high school diploma or equivalency certificate in the United States.

in that state, and in eight states, in-state institutions supply the majority of new PhDs to firms.

Table 2 displays inter-state and inter-regional migration data.[9] Several notable patterns become evident. Pacific states are major net importers of new PhDs; approximately 40% more PhDs have definite plans to work in California, Oregon and Washington than are produced there. California dominates in several respects. More PhDs going to industry are produced in California than in any other state, the state retains a higher percent of the PhDs it produces than does any other state, and more PhDs produced in other states head to California than to any other state. The strong presence of IT firms in Pacific states, especially during the period of study, as well as the heavy proportion of engineers in the database, no doubt contribute to this finding.

New England and Middle Atlantic states train approximately the same number of PhDs that they hire. If it were not for New Jersey, however, the Middle Atlantic region would be a net exporter. New Jersey's remarkable gain is in large part due to its ability to attract new PhDs from neighboring New York and Pennsylvania. New York provides other states or countries with 591 new industrial PhDs, sending 115 of those to New Jersey alone. Pennsylvania is not far behind, losing 518 new industrial PhDs to other areas -- 77 to New Jersey.

States in the Midwest (East North Central and West North Central) are net exporters, hiring approximately a third fewer PhDs than they train. The brain drain is substantial. As a region, the Midwest retains slightly more than a third of those trained, but retention within Midwestern states (as opposed to within the region) is considerably

[9] Six states, Alaska, Nevada, Hawaii, North Dakota, South Dakota, and Wyoming, either produced or received too few PhDs to report their inter-state migration numbers.

lower, averaging less than 28%. Indiana PhDs are the most likely to find employment in other states. Of the 376 new industrial PhDs graduating from Indiana universities in the three-year period, 46, a meager 12.2%, had definite plans to work for a firm in Indiana. Iowa is not far behind.

A state's ability to retain its highly-trained workers is largely contingent upon the strength of its metropolitan areas. More than 67% of new industrial PhDs who remain in-state work in the same consolidated metropolitan area (CMSA) in which they were trained. Table 3 takes a closer look at the ability of metropolitan areas to retain new industrial PhDs by examining the top 25 destination and the top 25 producing metropolitan areas.[10] Overall, slightly more than 70% of those trained in a CMSA were trained in a top-25 CMSA, while approximately 80% of those going to work in a metropolitan area go to a top-25 destination city. It is evident from Table 3 that areas that produce more industrial PhDs generally hire more PhDs in industry. This is accomplished by both retaining PhDs produced in the city and attracting PhDs from other cities. Eighteen metropolitan areas are in the top 25 in terms of both producing and employing new PhDs going to industry. Furthermore, slightly more than one out of every three PhDs trained in a top-25 metropolitan area stays in the area of training, whereas only about one in five produced in all other metropolitan areas stays where trained. This suggests that a dynamic is at work: Cities which produce more highly-skilled workers foster the development of new firms and attract firms wanting access to a highly-skilled

[10] Here we focus on PhDs awarded in a CMSA; 1027 of the new PhDs headed to industry were trained outside a CMSA. Note also that the number of PhDs produced in CMSAs is not equal to the number hired by a CMSA for three reasons: some work outside CMSAs in the United States, others leave the United States for industrial employment abroad, and others are trained outside a CMSA but work in a CMSA.

workforce. This in turn attracts more highly skilled workers from other areas and encourages retention of those trained in the area.

Particularly interesting is the role of New York/Northern New Jersey, San Francisco/San Jose, Boston, Los Angeles, and the District of Columbia/Baltimore. These five metropolitan areas (although not in the same order) represent the top five metropolitan areas, both in terms of destination *and* in terms of the production of PhDs heading to industry. Slightly over one in four of all new S&E PhDs headed to industry was trained in one of these five metropolitan areas, while approximately three out of eight were headed to one of these five metropolitan areas.[11]

Table 3 also shows that striking disparity exists in the ability of metropolitan areas to retain new industrial placements. The New York and San Francisco areas top the list; each employs about 58% of new industrial placements trained in their area. On the other hand, areas like Urbana-Champaign, Illinois, Lafayette, Indiana, and State College, Pennsylvania, all of which have a long tradition of training scientists and engineers, retain only about 3% of their new PhDs headed to industry. This high attrition rate demonstrates that the presence of a large university does not guarantee sufficient job opportunities in the industrial sector to retain S&E PhDs trained locally. Certainly, other factors necessary for economic development, such as transportation nodes, nearby

[11] The extreme geographic concentration displayed in Table 3 has been found using several other measures of innovation. For example, Black (2001) examined the geographic concentration of innovation using SBIR awards and patent counts. There is significant overlap with the PhD metropolitan areas: the top five metropolitan areas in terms of SBIR phase II awards are the same as the top five areas in terms of industrial PhDs produced and hired. Four of the five metropolitan areas are also in the top five in terms of utility patents issued (Chicago is fourth on the list, while the District of Columbia is eleventh).

amenities, access to venture capital, etc., present in cities like San Jose, are lacking in cities like Urbana-Champaign.[12]

While the universities like Illinois-Urbana/Champaign, Purdue and Pennsylvania State appear to have a low return on their investment in terms of the fact that new PhDs leave the city upon graduating, they do supply new talent to the state and nearby metropolitan areas. The University of Illinois-Urbana/Champaign supplies Chicago with about 10% of its new industrial hires, Purdue University is far and away the top supplier to Indianapolis, accounting for 21% of that city's industrial hires, and firms in Pennsylvania recruit 8 % of their new PhD talent from Pennsylvania State University.

Table 4 shows how migration behavior differs by a PhD's field of training. Thirty-six percent of engineers, who constitute about half of all industrial S&E hires in our sample, stay in state, while 26% have plans to stay in the same metropolitan area; both are close to mean of all S&E industrial hires. PhDs in agriculture have the lowest stay rates of all S&E fields, with about one in four staying in state, and less than one in ten with plans to work in the same metropolitan area they were trained in. This reflects in part the fact that PhDs in agriculture on temporary visas are the most likely of any group of S&E PhDs to leave the U.S. upon graduation (Black and Stephan 2003). By way of contrast, astronomers are the most likely to work in the state and metropolitan area in which they trained. More than 56% of astronomers have employment plans to work in the state of training and about 55% have plans to work in the metropolitan area of their doctoral institution.

[12] The lack of a booming industrial sector could prove an asset in the long run. That is, "college towns" may indirectly use their small city size as a tool to attract niche industries as well as a highly trained workforce, marketing the lack of disamenities that are present in cities with large industrial sectors, such as high crime rates, congestion, and air pollution.

Section VI: Empirical Results

In order to investigate specific factors affecting the decision to stay in the area of training, we estimate two equations, using two definitions of staying. In Equation 1 we estimate the probability that a new PhD has made a definite commitment to an industrial employer in the same state as their doctoral institution; the dependent variable in Equation 2 is whether or not the new PhD stays in the same primary metropolitan area.[13] Both equations are estimated using a logit model.

Table A.1 presents the definitions, means, and standard deviations for all variables included in the regressions. Table 5 provides the coefficients and z-statistics for the two equations. We restrict the analysis to PhDs trained in the continental United States, excluding those trained in Alaska, Hawaii and Puerto Rico. Table 5 also reports the marginal effects of a change in an independent variable, evaluated at the mean. For a dummy variable these marginal effects show by how much the probability will change with a change in status; in the case of a continuous variable, they show how much the probability will change with a one-unit change in the value of the variable. All PhDs who did not report their postdoctoral state of location or age are excluded from Equation 1; PhDs whose doctoral institution does not lie in a U.S. PMSA, as well as those who did not report a readable city name or age are excluded from Equation 2.

Table 5 shows that, other things being equal, the market for PhDs trained in certain fields is significantly less local than for other fields. Specifically, relative to the benchmark of biology, we find individuals trained in agriculture, engineering, chemistry,

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[13] The difference between CMSA and PMSA is one of size. Thus, while San Jose is a PMSA, the larger CMSA includes San Francisco and Oakland as well as San Jose. Because of issues related to confidentiality, we are not able to display the data at the PMSA level; however, we are able to analyze the data at this level.

computer science and earth science to be significantly more likely to leave the state of training. The effects, in many instances, are substantial, as can be seen by examining the marginal effects. With the exception of earth science, there are no significant differences at the PMSA level.

Few of the demographic variables play a significant role in determining whether the new PhDs stay in close geographic proximity to their institution of training. We do, however, find that Asians, as well as individuals who are underrepresented minorities in science and engineering (nonwhite, nonasian) are less likely to stay in the state or PMSA of training. The latter result may reflect the scarcity and hence wider market for underrepresented minorities receiving PhDs in science and engineering. Being a temporary resident is also a key factor in determining mobility. Compared to citizens, temporary residents are considerably more likely to leave the state as well as to leave the local area. The effect is fairly sizable. Other things being equal, temporary residents are about 6% more likely to leave either the state or local area than are citizens. Married PhDs are no more likely to remain in their location of training than are non-married PhDs; neither does the presence of children affect mobility, nor is mobility related to being a single parent. However, other things being equal, we find that married women are more likely to stay in state than are unmarried women. There is no indication, holding marital status constant, that women have differential mobility patterns than do men. We also find no support for the hypothesis that mobility decisions are responsive to the present value of moving; in neither instance do we find the coefficients on either age or age-squared to be significant.

Preferences as revealed through past mobility patterns play a significant role in determining the location decision. We find that doctorates who earned their PhD in the same state as their college degree are much more likely to remain in the PhD granting state than are those who changed states between college and graduate school. They are also more likely to stay in the same PMSA. The marginal effects are not inconsequential. Other things being equal, "stayers" are about 11% more likely to take an industrial position in state and 5% more likely to take a position in the city of training. At the state level we find that individuals who receive their PhD and college degree in the state from which they graduated high school are even more likely to remain in state than are those who moved to the state to get a college degree and stayed on to receive their PhD. At the PMSA level those who received their degree in the state in which they were born are significantly more likely to remain to take a position in industry. The policy implication is clear: accepting PhD students from in state significantly raises the probably of retention of the highly-skilled work force. At the margin, the cumulative effect of training PhDs who went to both high school and college in the state of doctoral training is 17%. For public institutions, this suggests that states capture part of their educational investment.

Variables that reflect wider access to networks are generally significant and with the expected sign. Individuals whose primary source of support was a fellowship or dissertation grant are significantly more likely to leave the state of training than the benchmark.[14] Individuals trained at top-rated programs[15] also are more likely to move,

[14] The benchmark is those whose primary source of support during graduate school was neither a fellowship nor dissertation grant, a teaching assistantship, a research assistantship or employer reimbursement.

although the effect is field dependent as well as dependent on the measure of mobility. In five of the ten fields studied (engineering, biology, chemistry, math and medicine), individuals trained at a top program are significantly more likely to leave their state than are individuals not trained at a top program in their field. And the marginal effects can be quite strong. Turning to Equation 2, we find that four of the top program variables are negative and significant as well, suggesting that in smaller geographical areas graduates from top programs leave as well.[16]

Individuals who worked full or part time during their last year of graduate school are assumed to have more information, other things being equal, concerning jobs in close proximity to their graduate institution. Our results support this hypothesis. We find that those working full or part time are more likely to stay in state and in the primary metropolitan area. The effects are large. For example, those who worked part time their last year in graduate school are 20% more likely to remain in state than are those who did not work part time and 14% more likely to remain in the same PMSA.

We also know from the SED whether a doctorate with definite plans is 'returning to or continuing in pre-doctoral employment.' Not surprisingly, PhDs who indicated they

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[15] Top fields are based on the 1995 National Research Council (NRC) rankings for all fields except medicine and agriculture. The rankings for the majority of fields are based on the "scholarly quality" scores in the NRC rankings for each relevant program at the institution. For field definitions that were broader than the program definitions in the NRC rankings (such as biology), we calculated the mean for each rated program applicable to our broader field for each institution. For the fields of medicine and agriculture, we used the 1998 NSF CASPAR data to rank institutions, due to the absence of data for these fields in the NRC rankings. Institutions in these fields were ranked by total federal R&D expenditures at each institution. In the case of biology and medicine, which have a very large number of PhD programs, 75 institutions were included among the top programs. For smaller fields, such as astronomy, the top category includes the top 25 programs. In most other fields, the top category includes the top 50 programs.

[16] The engineering, chemistry and math results persist when we restrict the definition of a top program to one that ranks in the top ten. In addition, using this more restrictive definition of quality, we find that individuals are more likely to leave the state of training if they matriculate from a top computer science or earth science program.

were returning to a previous employer are considerably more likely to remain where they were trained. The marginal effect is particularly strong at the state level (10%).[17]

Student debt level affects mobility, but not in the way hypothesized. Instead, we find the probability of remaining in one's location of training depends negatively upon the amount of debt accumulated in graduate school. This counter intuitive result may indicate that students who assumed debt engage in more search activity than do those with no debt, motivated by the need to find a highly remunerative position.

Finally, we are interested in knowing the degree to which the attributes of the local area affect the decision to leave the state or metropolitan area. Here we examine two dimensions of this relationship: the presence of innovative activity and the desirability of the state or local area, as proxied by per capita income and educational attainment.

At the state level, innovative activity is measured by the count of utility patents granted, as well as by industrial R&D expenditures and academic R&D expenditures.[18] In the PMSA equations we use the Milken index and patent counts as measures of innovative activity. In all instances, we control for population and land area. Generally speaking, we find that individuals coming from innovative areas are more likely to accept industrial employment locally. For example, the probability that an individual stays in the city of training is positively related to the number of utility patents granted in the city and the Milken Index.[19] At the state level, we find that individuals are more likely to stay

[17] A doctorate need not remain local, or even in state, to return to or continue in previous employment. In fact, 46 percent of new PhDs who indicate they are returning to or continuing in previous employment leave their state of training after graduation.

[18] Data on academic and industrial R&D expenditures come from the National Science Board (2002), and are computed in 1996 constant dollars for the years 1997, 1998 and 1999.

[19] The Milken Index, measured by the Milken Institute, is a measure of high-tech concentration in the PMSA. By definition, the Milken Index mean for the US is equal to 1.0. A metro area with an index

if the state has a high level of industrial R&D activity. Somewhat surprisingly, patent counts are not significant at the state level.

As a measure of employment opportunities for PhDs in the state (city) of training relative to elsewhere, we construct an index of the relative local absorptive capacity for PhD's ($ABPhD_i$), measured as the ratio of the flow of new PhDs produced locally to the stock of PhDs working in local industry relative to the same measure aggregated across the U.S. To wit, we define the measure as:

$$ABPhD_i = (NPhDI_i / PhDI_i)/(\Sigma NPhDI_i/\Sigma PhDI_i)$$

where $NPhDI_i$ is the number of new PhDs (in all fields) in location i (defined as either the state or PMSA) with plans to work in industry; $PhDI_i$ is the total number of all PhDs in location i working in industry. We hypothesize an inverse relationship. We find the variable to be negative and highly significant in predicting the probability that the individual will remain at either the state or local level. Clearly, the ability of the local area to absorb new PhDs is a prime factor in determining whether the individuals stay.

Our results also indicate that new PhDs are more likely to stay in their state of training the higher the per capita income in the area. Somewhat surprisingly, we do not find per capita income to be significant in the PMSA equation. In neither instance do we find the educational variables to be significant.[20]

If higher education were funded at the federal, rather than the state or local level, it would make little difference, from an economic development perspective, whether the newly trained PhDs remained local, or instead left the area of training. However, and as

higher than 1.0 has a higher high-tech concentration than the United States, a metro area with an index that is lower than 1.0 has a lower high-tech concentration.

[20] These results may reflect our failure to control for the relative values of these variables. Arguably, it is the relative value that affects the decision to stay or leave, not the level of the variable.

noted earlier, institutions of higher education in the U.S. are a mixed lot. Public institutions receive funding from the state, and indirectly, local area, in which they are located; private institutions do not. While we do not find a significant difference regarding the decision to stay in state between public and private institutions, we do find a significant difference at the PMSA level.

Given the important role that retention plays in leveraging public resources, we re-estimate the basic equations, focusing exclusively on public institutions. The results, presented in Appendix A.2, are reasonably similar to those presented in Table 5. The finding that many of the “best” PhDs leave persists when we focus exclusively on public institutions. Specifically, we find that individuals trained at top-rated biology, chemistry, computer science, math and medical PhD programs are less likely to remain in state than are those coming from non-top rated programs. Moreover, those who were supported on a fellowship or dissertation grant, an indicator of quality, are more likely to leave. PhD recipients from public institutions are more likely to remain in state if they received their undergraduate degree from the same state. Where one went to high school no longer matters when the sample is restricted to individuals who attended public institutions. The public PMSA results are reasonably similar to those for all institutions.

Section VII: Conclusion and Discussion

The movement of the highly educated from universities to firms is one mechanism by which knowledge is transferred. Despite the important role that industrial PhDs can play in economic development, to date we know very little regarding their location decisions. This knowledge gap is especially striking given the focus in recent years on the role that proximity plays in the transmission of knowledge (Feldman 1994;

Audretsch and Stephan 1996). To help rectify this deficiency, we measure the degree to which placements are local and what affects the likelihood that a PhD going to work in industry will remain in the same state or metropolitan area.

We find that states and local areas capture knowledge embodied in newly minted PhDs headed to industry, but not at an overwhelming rate. Only about one in three of those going to industry take a job in the state where trained; approximately one in five in the same PMSA. The averages, however, mask wide variations. California retained two out of three of the more than 1500 PhDs it trained for industry during the period. Indiana retained only one in eight of the 376 it trained. Wide variation exists at the metropolitan level as well: The San Francisco-Oakland-San Jose area retained almost 60% of those trained in the metropolitan area who take a position in industry as did the wider New York metropolitan area. By way of contrast, State College, Pennsylvania, retained about 3%, as did Champaign-Urbana, Illinois and Lafayette, Indiana.

Our research informs the question of whose knowledge is captured. We find that local areas are more likely to retain white students and students having little debt who are returning to a previous position. Being "home grown" predisposes one to remain as well. Those who receive their PhD in the same state as their undergraduate degree and high school degree are more likely to stay than are those who do not. Those who receive their PhD in the same state as their BA degree, as well as in their birth state are more likely to stay in the PMSA.

Graduates from certain fields are especially likely to leave the state: most notably agriculture, chemistry, engineering, computer science and earth science. Quality matters: top-rated PhD programs are often the ones that are most likely to produce graduates who leave the area. Those supported on fellowships or dissertation grants are more likely to leave the state of training. Graduates from private institutions are also more likely to find industrial employment outside the metropolitan area of training.

Not surprisingly, and consistent with a wide body of research on innovation, we find that local areas are more likely to retain new PhDs if the area is high in measures of innovation such as patent counts and R&D expenditures. The relative absorptive capacity of the local community also plays a major role. Champaign-Urbana graduates a large number of new PhDs who want to work in industry; yet relative to the U.S., few PhDs work in industry in the city.

Discussion.

Our results are consistent with the findings of Audretsch and Stephan (1996) concerning the degree to which knowledge is captured locally. To wit: they find only 30 percent of the scientist-firm links they examined to be local; we find that only 25 percent of new PhDs headed to industry stay in the MSA of training. There are at least two distinctions, however, between Audretsch and Stephan's work and this work. First, university faculty can be on multiple scientific advisory boards; new PhDs can only work for one firm at a time. Second, from the viewpoint of the university, it is entirely different to invest in faculty who establish ties with new firms out of the area while continuing to work at the university than to educate students who leave the area to take a position with a firm.

Our findings raise the larger question of whether the role of proximity to the university is overemphasized in the transmission of public knowledge from universities to industry. The top source of public knowledge, according to the Carnegie Mellon survey of firms (Cohen, Nelson, Walsh 2002), is publications and reports. Neither requires proximity to the scientist/engineer. The second source (informal information exchange, public meetings, or conferences and consulting) is facilitated by proximity but proximity is not essential. The next tier includes recently-hired graduate students. Our research shows that, in this respect, proximity does not play a major role.

We infer that if firms know what they are looking for, proximity to the university is not that important in the transmission of knowledge. Firms can search for the input. Proximity to the university is most important when the firm does not know what it is seeking or does not want to invest heavily in search or when the scientists involved in the transmission of tacit knowledge have a strong preference for remaining local, as Zucker, Darby and Brewer (1998) argue that star scientists had.[21]

States often invest in higher education with the conviction that it stimulates local economic development. And certainly research supports this conviction. Our work, however, casts doubt on the benefits states realize from one piece of this investment, the education of a doctoral scientific workforce, and suggests that states capture but a portion of the economic benefits resulting from a trained PhD workforce. What we don't investigate here is *why* states are able and willing to educate PhDs who leave after graduation. Is the knowledge and technology transfer produced while students are in graduate school sufficient to justify the expenditure? Do graduate students more than compensate for their educational costs, directly through tuition payments and indirectly

[21] This discussion raises the further question of the degree to which spillovers result from nonappropriability. We have argued that tacit knowledge comprises an important component of the knowledge that new PhDs transmit to firms. Yet tacit knowledge, as Zucker, Darby and Brewer (1998) point out, facilitates excludability. Thus knowledge transmission, to paraphrase the aforementioned authors, can result from the maximizing behavior of scientists who have the ability to appropriate the returns to this tacit knowledge rather than from nonappropriability.

through their labors in the classroom and the laboratory? Is the halo generated from having a top-rated program beneficial to the state in terms of general economic development? Is what we observe an indication of a disequilibrium which bleak budget prospects may hasten to adjust as state budgets for higher education are slashed? Can the Illinoises and Purdues continue to educate PhDs who overwhelmingly leave the state after graduation? Or are policy makers ignorant of the degree to which it is a leaky system?

Groen and White (2001, p. 24) note that incentives of universities and states with regard to the retention of highly-trained workers differ: "States have an interest in using universities to attract and retain high-ability individuals because they pay higher taxes and contribute more to economic development. Universities have an interest in their graduates being successful, but little interest in where their students come from or where they go after graduation." The distinction may be less clear in the post Bayh-Dole world, where public universities promote their science and engineering programs as engines of economic development. One wonders how long these institutions can continue to bake educational cake for other states and countries. The fact that in some instances the institutions are the major supplier of new in-state industrial hires may, of course, mitigate the political pressure to reallocate resources.

The implications drawn from this study are somewhat restricted due to the limited scope of the data. For example, the attractiveness of certain regions and cities may have been inflated during the time period of analysis. When we extend the analysis to years following the boom in information technology we may find a somewhat different picture than we do here.   Furthermore, the data eliminates PhDs who do not specify a firm as well as PhDs who eventually work in industry after taking a postdoc position. The percent of 'seasoned' PhDs going to industry is much larger than the percent of new PhDs choosing industry, particularly in the life sciences. As a result, if the study were done on location decisions five years following receipt of degree, as opposed to newly-minted PhDs, the conclusions might differ substantially.

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Table 1:
Firm Placements of New S&E PhDs by Field of Training:
1997-1999

Field	Percent of All PhDs Awarded that Identified a Firm	Percent In Field of PhDs that Identified a Firm
All S&E fields	14.5%	100% (n=10,121)
All Engineering	30.7%	53.0% (n=5,364)
Agriculture	9.0%	3.0% (n=308)
Astronomy	7.8%	0.4% (n=44)
Biology	3.8%	6.0% (n=609)
Chemistry	18.7%	12.0% (n=1,216)
Computer Science	28.4%	7.5% (n=762)
Earth Science	12.3%	2.5% (n=252)
Math	12.5%	4.7% (n=477)
Medicine	5.0%	4.3% (n=435)
Physics	16.1%	6.5% (n=654)

Table 2:
Inter-State and Inter-Regional Migration Patterns of New Industrial PhDs**
1997-1999

State/*Region*	Number of New PhDs Trained In State/*Region*	Number of New PhDs Working In State/*Region*	Percentage Gain or Loss	Number of New PhDs Produced that Stay In State/*Region*	Percent of New PhDs Produced that Stay In State/*Region*	Percent of New PhDs Imported from Other States/*Regions*
New England	***958***	***885****	***-7.6%***	***415***	***43.3%***	***53.1%***
Connecticut	145	220	51.7%	43	29.7%	80.5%
Maine	8	7	-12.5%	*s*	*s*	*s*
Massachusetts	713	594	-16.7%	259	36.3%	56.4%
New Hampshire	30	39	30.0%	9	30.0%	76.9%
Rhode Island	54	25	-53.7%	8	14.8%	68.0%
Vermont	8	*s*	*s*	*s*	*s*	*s*
Mid Atlantic	***1890***	***1998***	***5.7%***	***923***	***48.8%***	***53.8%***
New Jersey	311	766	146.3%	142	45.7%	81.5%
New York	898	801	-10.8%	307	34.2%	61.7%
Pennsylvania	681	431	-36.7%	163	23.9%	62.2%
East North Central	***2102***	***1346***	***-36.0%***	***794***	***37.8%***	***41.0%***
Illinois	611	441	-27.8%	179	29.3%	59.4%
Indiana	376	166	-55.9%	46	12.2%	72.3%
Michigan	430	308	-28.4%	142	33.0%	53.9%
Ohio	445	314	-29.4%	147	33.0%	53.2%
Wisconsin	240	117	-51.3%	45	18.8%	61.5%
West North Central	***698****	***504****	***-27.8%***	***244***	***35.0%***	***51.6%***
Iowa	168	47	-72.0%	27	16.1%	42.6%
Kansas	106	47	-55.7%	24	22.6%	48.9%
Minnesota	270	266	-1.5%	99	36.7%	62.8%
Missouri	97	109	12.4%	27	27.8%	75.2%
Nebraska	37	28	-24.3%	12	32.4%	57.1%
North Dakota	20	*s*	*s*	*s*	*s*	*s*
South Dakota	*s*	7	*s*	*s*	*s*	*s*
South Atlantic	***1692***	***1195****	***-29.4%***	***712***	***42.1%***	***40.4%***
Delaware	64	*s*	*s*	*s*	*s*	*s*
Florida	271	173	-36.2%	93	34.3%	46.2%
Georgia	324	171	-47.2%	91	28.1%	46.8%
Maryland	266	233	-12.4%	63	23.7%	73.0%
North Carolina	321	197	-38.6%	90	28.0%	54.3%
South Carolina	91	69	-24.2%	19	20.9%	72.5%
Virginia	269	233	-13.4%	81	30.1%	65.2%

West Virginia	23	35	52.2%	*s*	*s*	*s*
Washington D.C.	63	84	33.3%	7	11.1%	91.7%
East South Central	***297***	***193***	***-35.0%***	***97***	***32.7%***	***49.7%***
Alabama	102	56	-45.1%	28	27.5%	50.0%
Kentucky	46	37	-19.6%	*s*	*s*	*s*
Mississippi	49	12	-75.5%	*s*	*s*	*s*
Tennessee	100	88	-12.0%	40	40.0%	54.5%
West South Central	***896***	***1050***	***17.2%***	***491***	***54.8%***	***53.2%***
Arkansas	22	15	-31.8%	8	36.4%	46.7%
Louisiana	96	78	-18.8%	26	27.1%	66.7%
Oklahoma	96	49	-49.0%	27	28.1%	44.9%
Texas	682	908	33.1%	366	53.7%	59.7%
Mountain	***557****	***474****	***-14.9%***	***228***	***40.9%***	***51.9%***
Arizona	197	181	-8.1%	79	40.1%	56.4%
Colorado	196	154	-21.4%	73	37.2%	52.6%
Idaho	12	29	141.7%	*s*	*s*	*s*
Montana	15	9	-40.0%	*s*	*s*	*s*
New Mexico	41	38	-7.3%	16	39.0%	57.9%
Utah	85	47	-44.7%	27	31.8%	42.6%
Nevada	*s*	14	*s*	*s*	*s*	*s*
Wyoming	11	*s*	*s*	*s*	*s*	*s*
Pacific	***1831****	***2534***	***39.7%***	***1270***	***69.4%***	***50.2%***
Alaska	*s*	*s*	*s*	*s*	*s*	*s*
California	1539	2126	38.1%	1043	67.8%	50.9%
Oregon	99	*s*	*s*	40	*s*	*s*
Washington	161	187	16.1%	57	35.4%	69.5%
Hawaii	15	*s*	*s*	*s*	*s*	*s*
Other						
Puerto Rico	17	18	5.6%	13	76.5%	27.8%
Sum/means US	*10932*	*10303*	*n/a*	*n/a*	*n/a*	*n/a*

s=suppressed. At the request of Science Resources Statistics, National Science Foundation, counts not reported if 6 or less or if a specific firm contributes half or more of the count in a cell.

*Suppressed cells not included in sums to prevent identification of cells.
**Counts include PhDs trained in Economics and Psychology.

Table 3:
Top 25 Producing and Destination Consolidated Metropolitan Areas: **
1997-1999

Top 25 Producing Consolidated Metropolitan Areas				TOP 25 Destination Consolidated Metropolitan Areas			
Consolidated Metropolitan Area	N	# that stay	% that stay	Consolidated Metropolitan Area	N	# Local	% Local
New York-No. New Jersey-Long Island, NY-NJ-CT-PA	732	423	57.8%	San Francisco-Oakland-San Jose, CA	1369	416	30.4%
San Francisco-Oakland-San Jose, CA	706	416	58.9%	New York-No. New Jersey-Long Island, NY-NJ-CT-PA	1293	423	32.7%
Boston-Worcester-Lawrence-Lowell-Brockton, MA-NH NE	614	238	38.8%	Boston-Worcester-Lawrence-Lowell-Brockton, MA-NH NE	588	238	40.5%
Los Angeles-Riverside-Orange County, CA	525	233	44.4%	Los Angeles-Riverside-Orange County, CA	484	233	48.1%
Washington-Baltimore, DC-MD-VA-WV	327	160	48.9%	Washington-Baltimore, DC-MD-VA-WV	443	160	36.1%
Champaign-Urbana, IL	313	10	3.2%	Houston-Galveston-Brazoria, TX	340	48	14.1%
Detroit-Ann Arbor-Flint, MI	304	102	33.6%	Chicago-Gary-Kenosha, IL-IN-WI	339	122	36.0%
Chicago-Gary-Kenosha, IL-IN-WI	290	122	42.1%	Portland-Seattle-Tacoma, OR-WA	339	68	20.1%
Atlanta, GA	282	73	25.9%	Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD	296	86	29.1%
Austin-San Marcos, TX	282	67	23.8%	Dallas-Fort Worth, TX	273	46	16.8%
Lafayette, IN	279	8	2.9%	Detroit-Ann Arbor-Flint, MI	241	102	42.3%
Minneapolis-St. Paul, MN-WI	266	86	32.3%	Minneapolis-St. Paul, MN-WI	233	86	36.9%
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD	263	86	32.7%	Austin-San Marcos, TX	182	67	36.8%
Pittsburgh, PA	217	42	19.4%	San Diego, CA	159	55	34.6%
State College, PA	209	7	3.3%	Atlanta, GA	150	73	48.7%
Madison, WI	208	16	7.7%	Raleigh-Durham-Chapel Hill, NC	144	51	35.4%
Raleigh-Durham-Chapel Hill, NC	178	51	28.7%	Phoenix-Mesa, AZ	121	35	28.9%
Portland-Seattle-Tacoma, OR-WA	162	68	42.0%	Denver-Boulder-Greeley, CO	120	54	45.0%
Columbus, OH	154	21	13.6%	Cincinnati-Hamilton, OH-KY-IN	109	27	24.8%
Denver-Boulder-Greeley, CO	144	54	37.5%	Albany-Schenectady-Troy, NY	105	24	22.9%
Greensboro--Winston-Salem--High Point, NC	142	*s*	*s*	Pittsburgh, PA	101	42	41.6%
Albany-Schenectady-Troy, NY	138	24	17.4%	Cleveland-Akron, OH	96	42	43.8%
Cleveland-Akron, OH	138	42	30.4%	Indianapolis, IN	81	0	0.0%
Tucson, AZ	127	24	18.9%	St. Louis, MO-IL	81	25	30.9%
San Diego, CA	122	55	45.1%	Rochester, NY MSA	63	17	27.0%
Sum Top 25 Metropolitan Areas	7122	2427*	34.1%	Sum Top 25 Metropolitan Areas	7750	2540	32.8%
All Other Metropolitan Areas	2783	564	20.3%	All Other Metropolitan Areas	1812	453	25.0%

s=suppressed. Counts of 6 or less not reported at the request of Science Resources Statistics, National Science Foundation.
*Suppressed count not included in total to prevent identification of the suppressed count.
**Counts include PhDs trained in Economics and Psychology.

Table 4:

Percent of Firm Placements Staying In State
and Consolidated Metropolitan Areas by Field of Training:
1997-1999

Field	% Staying In State	% Staying In CMSA
All Engineering	36.3%	26.2%
Agriculture	26.0%	9.7%
Astronomy	56.8%	54.5%
Biology	45.0%	34.6%
Chemistry	28.6%	19.7%
Computer Science	36.4%	30.6%
Earth	28.6%	17.9%
Math	35.0%	29.4%
Medicine	46.0%	35.2%
Physics	45.0%	35.0%
All Fields	36.4%	26.6%

Table 5:
Empirical Results
Sample = Placements Trained in the Continental U.S.

	Equation (1): Dependent Variable = SameSTATE (N=10,000)				Equation (2): Dependent Variable = SamePMSA (N=8,838)		
Variable	Estimate	z-stat[1]	Marginal Effect		Estimate	z-stat[1]	Marginal Effect
Intercept	-3.4812***	17.71	n/a		-3.2185***	12.43	n/a
age	0.0634	2.58	0.0142		0.0637	1.93	0.0091
agesq	-0.0004	0.63	n/a		-0.0004	0.41	n/a
female	-0.0875	0.83	-0.0196		-0.0785	0.45	-0.0112
asian	-0.1498**	5.11	-0.0336		-0.2897***	13.84	-0.0412
nonwhite_asian	-0.2188**	4.77	-0.0478		-0.2385**	4.02	-0.0323
permres	0.1335	2.28	0.0306		-0.0296	0.08	-0.0043
tempres	-0.2913***	16.82	-0.0647		-0.4297***	25.55	-0.0597
married	0.0671	1.15	0.0151		0.0952	1.61	0.0137
female_married	0.2413*	3.82	0.0559		0.0947	0.41	0.0141
wchild	0.0019	0.01	0.0004		-0.0034	0.01	-0.0005
singlepar	-0.1479	1.09	-0.0326		-0.1113	0.44	-0.0156
samece_phd	0.4742***	21.01	0.1112		0.3410***	8.63	0.0530
samehs_phd	0.2609*	3.18	0.0605		-0.1956	1.41	-0.0270
sameb_phd	0.0747	0.31	0.0170		0.2966**	3.89	0.0465
return	0.4428***	37.99	0.1036		0.3455***	17.63	0.0537
debtlevel	-0.0057**	6.01	-0.0013		-0.0078***	7.55	-0.0011
preftemp	0.4087***	46.49	0.0941		0.3443***	22.57	0.0521
preptemp	0.8163***	68.47	0.1974		0.8029***	55.42	0.1432
supp_fellow	-0.2600***	8.32	-0.0567		-0.1616	2.33	-0.0225
supp_teachasst	0.0325	0.14	0.0074		-0.0393	0.14	-0.0057
supp_RA_trainee	-0.1125	2.54	-0.0254		-0.0570	0.47	-0.0083
supp_employer	0.0550	0.23	0.0125		0.0274	0.05	0.0040
astr	0.2647	0.21	0.0619		-0.2034	0.09	-0.0276
agri	-0.8708**	5.62	-0.1660		-0.6840	0.99	-0.0796
alleng	-0.3713**	4.43	-0.0839		-0.0348	0.03	-0.0051
chem	-0.6905***	12.12	-0.1407		-0.2954	1.65	-0.0398
math	-0.2930	1.67	-0.0631		0.1751	0.45	0.0267
comp	-0.5299**	5.97	-0.1099		-0.1990	0.66	-0.0273
earth	-1.1897***	12.94	-0.2093		-1.2719***	8.67	-0.1226
medi	-0.2376	1.04	-0.0516		-0.1371	0.28	-0.0191
phys	-0.2280	1.09	-0.0497		0.0895	0.13	0.0133
topsastr	-0.1078	0.02	-0.0239		0.4210	0.29	0.0695
topsagri	0.0107	0.01	0.0024		-0.1003	0.02	-0.0141
topsalleng	-0.2423***	10.88	-0.0541		-0.3268***	12.89	-0.0464
topsbiol	-0.4438**	4.98	-0.0929		-0.2406	1.15	-0.0325
topschem	-0.3724**	6.52	-0.0794		-0.4651**	6.49	-0.0592
topscomp	-0.2738	2.41	-0.0592		-0.1882	0.87	-0.0258
topsearth	-0.0394	0.01	-0.0088		0.0297	0.00	0.0044
topsmath	-0.4171*	3.82	-0.0875		-0.1820	0.55	-0.0249

topsmedi	-0.5861***	6.72	-0.1187		-0.5087**	3.97	-0.0627
topsphys	0.1874	1.08	0.0433		0.1474	0.49	0.0223
private	0.0445	0.60	0.0101		-0.1814**	6.00	-0.0258
STpats	-0.00041	0.54	-0.000092		n/a	n/a	n/a
STacadRD	-0.000020	0.30	-0.000004		n/a	n/a	n/a
STindRD	0.000026***	11.85	0.000006		n/a	n/a	n/a
STsize	0.000058***	68.53	0.000013		n/a	n/a	n/a
STpop	-0.00012	0.45	-0.00003		n/a	n/a	n/a
STperhe	0.0098	0.63	0.0022		n/a	n/a	n/a
STpcinc	0.0413**	4.37	0.00933		n/a	n/a	n/a
ABPhDST	-0.2286***	7.54	-0.0516		n/a	n/a	n/a
pmsapats	n/a	n/a	n/a		0.00295***	21.45	0.00043
milkenind	n/a	n/a	n/a		0.3645***	33.59	0.0529
pmsapop	n/a	n/a	n/a		0.00009***	33.53	0.000014
pmsasize	n/a	n/a	n/a		0.0333**	5.36	0.0048
pmsapcinc	n/a	n/a	n/a		0.0030	0.11	0.00043
pmsaperhe	n/a	n/a	n/a		-0.0084	1.74	-0.0012
ABPhDMSA	n/a	n/a	n/a		-0.0966***	47.63	-0.0140
-2 Log-likelihood	13117.0				9496.5		

[1] z-stats are based on chi-square distribution

* (**) [***] Statistically significantly different from zero at the 10% (5%) [1%] level of significance.

Appendix

Table A.1:
Variable Definitions and Descriptive Statistics

Dependent Variables	*Definition*	*Mean (Std Dev)*	*Same State (Eq. 1)*	*Same PMSA (Eq. 2)*
SameSTATE	Dummy variable indicating whether or not an individual has definite plans to remain in the same state in which they earned their PhD	0.367 (0.482)	XX	
SamePMSA	Dummy variable indicating whether or not an individual has definite plans to remain in the same PMSA in which they earned their PhD	0.209 (0.4064)		XX
Independent Variables	*Definition*			
age	Age of the individual at the time of PhD	32.52 (5.043)	X	X
agesq	Age of the individual squared	1083.0 (373.94)	X	X
female	Dummy variable indicating whether or not an individual is a female	0.202 (0.401)	X	X
white*	Dummy variable indicating whether or not an individual is White	0.555 (0.497)	X	X
asian	Dummy variable indicating whether or not an individual is Asian or Pacific Islander	0.378 (0.485)	X	X
nonwhite_asian	Dummy variable indicating whether or not an individual is a race other than White or Asian	0.065 (0.246)	X	X
permres	Dummy variable indicating whether or not an individual is a permanent resident in the U.S.	0.105 (0.306)	X	X
tempres	Dummy variable indicating whether or not an individual is a temporary resident in the U.S.	0.333 (0.471)	X	X
married	Dummy variable indicating whether or not an individual is married.	0.613 (0.487)	X	X
female_married	Dummy variable indicating whether or not an individual is a married female	0.111 (0.315)	X	X
wchild	Dummy variable indicating whether or not an individual is married with at least one dependent	0.245 (0.430)	X	X
singlepar	Dummy variable indicating whether or not an individual is not married with at least one dependent	0.030 (0.170)	X	X
samece_phd	Dummy variable indicating whether or not an individual earned their PhD in the same state they went to college	0.182 (0.386)	X	X
samehs_phd	Dummy variable indicating whether or not an individual went to high school, college and earned their PhD in the same state	0.129 (0.336)	X	X
samebirth_phd	Dummy variable indicating whether or not an individual was born, went to high school, college, and earned their PhD in the same state	0.085 (0.279)	X	X
return	Dummy variable indicating whether or not an individual has definite plans to continue in or return to previous employer	0.196 (0.397)	X	X
debtlevel	Individual's reported debt level in thousands, measured in $5,000 intervals, at the time of degree.	6.776 (10.76)	X	X
preftemp	Dummy variable indicating whether or not an individual was employed full-time one year prior to receipt of PhD	0.324 (0.468)	X	X
preptemp	Dummy variable indicating whether or not an individual was employed part-time one year prior to receipt of PhD	0.066 (0.248)	X	X
pre_otheremp*	Dummy variable indicating whether or not an individual was anything other than full or part time employed one year prior to PhD	0.035 (0.183)	X	X

supp_fellow	Dummy variable indicating whether or not individual's primary source of support during graduate school was fellowship or dissertation grant	0.133 (0.340)	X	X
supp_teachasst	Dummy variable indicating whether or not individual's primary source of support during graduate school was teaching assistantship	0.148 (0.355)	X	X
supp_RA_train	Dummy variable indicating whether or not individual's primary source of support during graduate school was research assistantship, internship, or traineeship	0.479 (0.500)	X	X
supp_employer	Dummy variable indicating whether or not individual's primary source of support during graduate school was employer reimbursement or assistance	0.050 (0.219)	X	X
supp_other*	Dummy variable indicating whether or not individual's primary source of support during graduate school was anything other than employer, research or teaching assistant, trainee, diss. grant or fellowship	0.189 (0.392)	X	X
astr	Dummy variable indicating whether or not an individual's field of training was astronomy	0.004 (0.063)	X	X
agri	Dummy variable indicating whether or not an individual's field of training was in agriculture	0.030 (0.165)	X	X
alleng	Dummy variable indicating whether or not an individual's field of training was engineering	0.530 (0.500)	X	X
biol*	Dummy variable indicating whether or not an individual's field of training was biology	0.060 (0.229)	X	X
chem	Dummy variable indicating whether or not an individual's field of training was chemistry	0.121 (0.314)	X	X
comp	Dummy variable indicating whether or not an individual's field of training was computer science	0.075 (0.255)	X	X
earth	Dummy variable indicating whether or not an individual's field of training was earth science	0.025 (0.150)	X	X
math	Dummy variable indicating whether or not an individual's field of training was mathematics	0.047 (0.204)	X	X
medi	Dummy variable indicating whether or not an individual's field of training was medicine	0.043 (0.195)	X	X
phys	Dummy variable indicating whether or not an individual's field of training was physics	0.065 (0.237)	X	X
topsastr	Dummy variable indicating whether or not an individual's PhD field was astronomy and their PhD institution was top ranked in astronomy	0.003 (0.051)	X	X
topsagri	Dummy variable indicating whether or not an individual's PhD field was agriculture and their PhD institution was top ranked in agriculture	0.023 (0.149)	X	X
topsalleng	Dummy variable indicating whether or not an individual's PhD field was in engineering and their PhD institution was top ranked in engineering	0.354 (0.478)	X	X
topsbiol	Dummy variable indicating whether or not an individual's PhD field was biology and their PhD institution was top ranked in biology	0.039 (0.193)	X	X
topschem	Dummy variable indicating whether or not an individual's PhD field was chemistry and their PhD institution was top ranked in chemistry	0.068 (0.251)	X	X
topscomp	Dummy variable indicating whether or not an individual's PhD field was computer science and their PhD institution was top ranked in computer science	0.046 (0.210)	X	X
topsearth	Dummy variable indicating whether or not an individual's PhD field was earth science and their PhD institution was top ranked in earth science	0.016 (0.124)	X	X
topsmath	Dummy variable indicating whether or not an individual's PhD field was mathematics and their PhD institution was top ranked in mathematics	0.024 (0.154)	X	X
topsmedi	Dummy variable indicating whether or not an individual's PhD field was medicine and their PhD institution was top ranked in medicine	0.021 (0.142)	X	X
topsphys	Dummy variable indicating whether or not an individual's PhD field was physics and their PhD institution was top ranked in physics	0.037 (0.189)	X	X
private	Dummy variable indicating whether or not an individual received their PhD from a private institution	0.324 (0.468)	X	X
STpats	Number of patents in thousands granted in the state of the individual's PhD institution between 1997-1999	6.49 (6.66)	X	

STacadrd	Academic R&D expenditures in millions in the state of the individual's PhD institution between 1997-1999 in thousands of 1996 dollars	36.539 (28.465)	X	
STindrd	Industrial R&D expenditures in millions in the state of the individual's PhD institution between 1997-1999 in thousands of 1996 dollars	28.631 (32.568)	X	
STsize	Geographic size in thousands of square miles of the state of the individual's PhD institution	75.852 (66.31)	X	
STpop	Population in hundred thousands in 2000 in the state of the individual's PhD institution	129.696 (99.816)	X	
STperhe	Percent of the population age 25+ in the state of the individual’s PhD institution with a bachelor’s degree or higher in 1998	25.22 (4.06)	X	
STpcinc	Per Capita income in thousands in the state of the individual’s PhD institution in 1994	22.953 (2.570)	X	
ABPhDST	PhD absorption capacity index in the state of the individual’s PhD institution (see text)	1.129 (0.400)	X	
pmsapats	Number of patents in hundreds granted in the PMSA of the individual's PhD institution between 1997-1999	8.17 (8.68)		X
milkenind	Milken Index in the PMSA of the individual’s PhD institution in 2002	1.110 (0.711)		X
pmsasize	Geographic size in thousands of square miles of the PMSA of the individual's PhD institution	2.464 (2.116)		X
pmsapop	Population in hundred thousands in the PMSA of the individual's PhD institution in 2000	25.22 (26.54)		X
pmsaperhe	Percent of the population age 25+ in the PMSA of the individual’s PhD institution with a Bachelor’s degree or higher in 2000	31.572 (6.92)		X
pmsapcinc	Per capita income in thousands in the PMSA of the individual’s PhD institution in 1999	31.62 (5.863)		X
ABPhDMSA	PhD absorption capacity index in the PMSA (see text)	3.547 (4.41)		X

* Indicates the benchmark or control group.
‘XX’ Means the variable is a dependent variable included in the equation
‘X’ Means the variable is an explanatory variable included in the equation

Table A.2:
Empirical Results
Sample = Placements Trained in the Continental U.S. in a Public Institution

	Equation (1): Dependent Variable = SameSTATE		Equation (2): Dependent Variable = SamePMSA	
	N=6,832		N=5,973	
Variable	Estimate	z-stat[1]	Estimate	z-stat[1]
Intercept	-4.0254***	16.16	-3.2767***	7.77
age	0.0759	2.49	0.0980*	2.77
agesq	-0.0005	0.69	-0.0007	0.91
female	-0.0152	0.01	-0.1222	0.55
asian	-0.1433*	2.83	-0.3627***	11.41
nonwhite_asian	-0.1187	0.92	-0.1546	1.00
permres	0.0224	0.04	-0.2446*	3.00
tempres	-0.3443***	14.26	-0.5355***	20.95
married	0.0742	0.87	0.1158	1.29
female_married	0.0971	0.39	0.1595	0.62
wchild	0.0633	0.64	0.0795	0.66
singlepar	-0.3512**	3.95	-0.3785	2.65
samece_phd	0.5645***	16.37	0.2367	2.00
samehs_phd	0.1983	1.22	-0.1240	0.34
sameb_phd	0.0685	0.20	0.4018**	5.13
return	0.5790***	44.55	0.3927***	14.19
debtlevel	-0.0078***	7.12	-0.0103***	7.61
preftemp	0.4254***	33.27	0.4280***	20.29
preptemp	0.6526***	31.95	0.7237***	29.67
Supp_Fellow	-0.4007***	11.50	-0.1308	0.78
Supp_TeachAsst	0.0711	0.46	0.0886	0.44
Supp_RA_Trainee	-0.1450*	2.95	-0.0018	0.00
Support_Employer	0.1579	1.21	0.0406	0.07
astr	1.0445	1.69	0.0444	0.00
agri	-0.8062**	4.17	-0.5502	0.61
alleng	-0.4062*	3.23	-0.1667	0.40
chem	-0.6081**	5.92	-0.4540	2.24
math	-0.1447	0.28	0.0567	0.03
comp	-0.4831*	3.06	-0.2341	0.52
earth	-1.1193***	9.58	-1.2857***	7.64
medi	-0.1585	0.28	-0.0339	0.01
phys	-0.0379	0.02	0.1738	0.28
topsastr	-0.7449	0.50	0.0949	0.01
topsagri	-0.0336	0.01	-0.5447	0.59
topsalleng	-0.1305	1.97	-0.3363***	6.87
topsbiol	-0.4799*	3.45	-0.5912*	3.82
topschem	-0.4939***	7.67	-0.5684**	5.45
topscomp	-0.4295*	3.68	-0.6812**	6.08
topsearth	0.1426	0.15	-0.0452	0.01

topsmath	-0.7983***	8.90		-0.4819	2.23
topsmedi	-0.6370**	5.23		-0.8052**	5.56
topsphys	0.0418	0.03		0.1081	0.15
STpats	0.00025	0.18		n/a	n/a
STacadRD	-0.00010**	4.42		n/a	n/a
STindRD	0.000021**	5.90		n/a	n/a
STsize	0.0062***	54.98		n/a	n/a
STpop	-0.000014	0.48		n/a	n/a
STperhe	0.0046	0.11		n/a	n/a
STpcinc	0.0001**	5.88		n/a	n/a
ABPhDST	-0.2538***	7.26		n/a	n/a
pmsapats	n/a	n/a		0.0010***	59.81
milkenind	n/a	n/a		0.4875***	33.36
pmsapop	n/a	n/a		0.0000038	0.02
pmsasize	n/a	n/a		0.02050	1.59
pmsapcinc	n/a	n/a		-0.03060**	6.56
pmsaperhe	n/a	n/a		-0.0070	0.66
ABPhDMSA	n/a	n/a		-0.0789***	27.56
-2 Log-likelihood	8857.6			5869.2	

[1] z-stats are based on chi-square distribution

* (**) [***] Statistically significantly different from zero at the 10% (5%) [1%] level of significance.