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 an important means by which knowledge is transferred from the university and by which university-industry networks are built and reinforced. 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, or leave after receipt of degree. The policy relevance of the question is obvious, given that a common lever by which public funds are raised for universities is the prospect of local economic growth.

This paper examines factors that influence the probability that a newly trained PhD will remain "local" or stay in the 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 of training. Given that the ability to capture knowledge spillovers arguably decreases as distance increases, we also examine the distance new PhDs move to take an industrial position. Our study focuses on PhDs who received their degree in one of twelve 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. Moreover, the related universities are not new but have a long history of producing scientists and engineers. This suggests that training local talent is far from sufficient in fostering an economic environment that encourages retention. We also find that retention is related to a number of personal characteristics such as marital status, age, level of debt, previous work experience and visa status. Retention is also related to the local technological infrastructure.

Section I. Introduction

Doctoral students are a key mechanism by which universities and firms interface. It is not uncommon for graduate students, while in school, to work on industry-sponsored research as well as to work directly in industrial labs. But for PhDs who go to work for industry, the keystone of the interface occurs at the time of graduation. Their placement with industry provides a means by which knowledge is transferred from the university, and by which networks are built and reinforced. This means of knowledge transfer can be especially important in facilitating the movement of tacit knowledge.

Despite the role that new PhDs play in transmitting knowledge, 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. forthcoming). 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.

[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.

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 herald the role they play in local economic development, mindful of Stanford's role in the creation of Silicon 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. Appropriations to higher education institutions have always been highly volatile, moving in direct relation to a state's economic output. In today's economic environment, state policymaker's are especially concerned with the appropriateness of their investment in higher education.[3]

The stakes are somewhat different for private 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. Moreover, keeping their graduates close to home can enhance connections with the university that create a strong alumni base.

This is not to say that universities are solely focused on keeping industrial graduates close at hand. Placements outside the local area are an indication of success,

[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 faculty often don't know the name of the firms their students go to work for.

[3] Austin Gilbert of South Carolina's Commission on Higher Education said, "South Carolinians have come to doubt that public colleges are using their tax dollars wisely … and this has made lawmakers reluctant to spend more on higher education." (Robst 2001, p. 730).

signaling that the university has the necessary connections and reputation to warrant more distant placements.[4] Moreover, strong industrial placements, regardless of whether or not they are local, can enhance future funding opportunities with industry.

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 of training. We are also interested in the distance new PhDs move to take an industrial position given that the ability to capture knowledge spillovers arguably decreases as distance increases. Our study focuses on PhDs who received their degree in one of twelve fields in science and engineering (S&E) during the period 1997-1999. Data 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. Only about three in eight of those going to industry take a job in the state where trained; approximately one in four remain in the same consolidated metropolitan statistical area (CMSA); one in five in the same primary metropolitan statistical area (PMSA).[5] The averages, however, mask wide variations. The San Francisco-Oakland-San Jose area retains approximately 60% of those trained; the Lafayette, Indiana, CMSA retains approximately 3% as do Champagne-

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

[5] A CMSA is defined as an MSA that has separate component urban areas and has a population of one million or more residents within the consolidated area. Counties are used to define the consolidated metropolitan statistical areas except in New England where cities and towns are used. By way of contrast, a PMSA is defined as the urban component area within the CMSA. In the case when a metropolitan area does not have separate urban components, such as Atlanta, Georgia, the CMSA level and the PMSA level of observation is the same and of equal size.

Urbana, Illinois and State College, Pennsylvania. At the state level, California retains two in three; Indiana retains one in eight.

Local areas are more likely to retain older students, married students and students who have little debt, especially if they are returning to a previous job. Being "home grown" helps as well. Those who did not leave the state of undergraduate training for PhD training are more likely to stay and those who went to college and got their PhD in the same state from which they graduated from high school are even more likely to stay in the state. They also move a shorter distance if they leave the PMSA. By contrast, those who studied on a temporary visa are exceedingly likely to move, both out of the metropolitan area and out of the state.

The technological environment in the local area plays a key role. Individuals are more likely to stay in close proximity to their alma mater if the alma mater is located in an innovative area, as indicated by such measures as patent counts, R&D expenditures and the Milken Index. Work experience also plays a major role in retention. Individuals returning to a position they had prior to receiving the Ph.D. are less likely to leave the state or metropolitan area, as are those who worked either part or full time the last year in graduate school.

The paper proceeds as follows. Section II provides a discussion of the role new PhDs play in knowledge transfer. Section III offers a conceptual model of the individual decision to migrate and summarizes some of the literature on determinants and consequences of migration. Section IV 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 V gives the results from our empirical analyses and discusses the policy implications. Section VI concludes by summarizing the key findings and future research agenda.

Section II: The Role of New Ph.D.s 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. [6]

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 obtained knowledge from the public sector.

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

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.[7]

In a related study, Agrawal and Henderson (2002) interviewed 68 engineers 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%. Recruitment of MIT graduates was a close third at 16.8%.

Despite the fact that placements of new Ph.D.s play a role in the university-industry interface, empirical studies of knowledge transfer between the public and private sectors consistently use other measures as proxies for knowledge availability or the potential of knowledge transfer. Early work by Jaffe (1989), for example, used university research and development expenditures as a proxy for knowledge spillovers as did work by Audretsch and Feldman (1996a, 1996b). More recent work by Feldman and Audretsch (1999),

[7] 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.

Anselin, Varga and Acs (1997, 2000) and Black (2001) has followed suit, shifting the analysis, however, from the state to the CMSA. Other studies of knowledge transfer between the public and private sectors focus on flows of codified knowledge, using, for example, article counts or patent citations to articles written in the academic sector. Adams (1990) finds the effects of publications to be important to productivity in the manufacturing sector, though in the case of publications coming from basic sciences the lag is approximately 20 years. Deng, Lev and Narin (1999) report a strong connection between a firm's patent citations to articles written in the academic sector and the firm's market-to-book value. Narin, Hamilton and Olivastro (1997) show that over 70% of papers cited in U.S. industry patents come from public science.

One of the few papers to focus specifically on scientists as a measure of spillovers was written by Audretsch and Stephan (1996) and examines academic scientists affiliated with a biotech company. Because the authors knew the location of both the scientist and the firm, they were 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 tie is local. Here we extend the Audretsch-Stephan framework, examining the location decisions of recent graduates.

Section III: 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, as greater than the costs, composed of both pecuniary and psychic costs to moving. Borjas et. al. (1992) extend the investment decision to include the relative returns to skills in a state. They assume that individuals choose the state that is most likely to maximize income, which allows them to measure the returns to skill in a state via observing the extent of earnings inequality in a state. By examining state of high school education versus state of employment for individuals of various skill levels, they find that skilled workers are more likely to leave a state that has low inequality and move to a state with higher inequality, while unskilled workers have the propensity to do the opposite. Mueser and Graves (1995) have focused on the role of amenities in migration decisions by calculating migratory elasticities with respect to local amenities and geographic attributes, such as access to recreational areas and a warm climate.

Most previous studies that examine the determinants of migration use aggregate data, examining the relationship between various region-specific characteristics and gross or net migration rates between regions. While such analyses are useful in judging the importance of locational characteristics, they can camouflage many important personal characteristics, such as one's marital status or field of training, and thus offer limited insight into how personal characteristics affect location choice. In order to understand the deterministic relationship between choice of location and individual characteristics in the migratory decision process, one must combine/compare individual data with location data, an advantage this study can provide.[8]

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[8] Many of these aggregate studies also do not differentiate among the highly educated, telling us only part of the story with regard to which regions are net gainers or losers in terms of human capital. That is, even

Here we are interested in modeling the decision of a PhD headed to industry to locate outside 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 and, conditional on moving, how far the PhD moves. In the binary choice models, we are interested in three sets of explanatory variables: 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, institutional characteristics and the R&D status of the hiring firm. In the conditional distance equation, we include only the latter two sets of variables. From a policy perspective, we are also interested in knowing whether individuals trained at a

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if a state or region is a net exporter of population, it can be a net importer of human capital if it is importing larger proportions of the highly educated and exporting less educated people. Greenwood (1986) offers a good example. He argues that although the South was a net exporter in terms of the general population during the 1950s and 1960s, it was a net importer of human capital because non-native college graduates strongly favored the South. The net increase in human capital may have played a vital role in the South's subsequent economic growth. Studying the migratory patterns of PhDs, who arguably have the highest amount of human capital, can serve to indicate whether regions are net importers or exporters of human capital.

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 are measured in terms of the degree of innovative activity 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. Personal characteristics affecting present value include age, marital status and number of dependents. Variables that reflect wider access to networks include the NRC rank of the department as well as whether or not the individual was supported on a fellowship during graduate school. By way of contrast, we expect individuals who worked 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 IV: 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 98%. While the SED has always asked graduates to provide information concerning industrial placements, the identity 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 and determine whether the new PhD was placed at a top 200 R&D firm (or subsidiary) 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.[9] 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.[10]

The fields of training of the 10,932 new PhDs with definite plans to work in industry are given in Table 1. Not surprisingly, the data is dominated by large fields

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[9] 17,382 of the 75,243 PhDs awarded in S&E 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.

[10] In order to make inferences as to the migration decision of all PhDs going to industry, we should first account for sample selection bias which could result from excluding those without definite plans from the analysis. In a future version of this paper we plan to address this issue.

having a tradition of working in industry as well as a tradition of not accepting a post doc position prior to heading to industry. Forty-nine percent of the sample is made up of engineers; 11% of chemists.

For the 10,932 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. While the overall percent of industrial PhDs that stay in state may seem low, this 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 to firms in that state, and in eight states, in-state institutions supply the majority of new PhDs to firms.

Table 2 looks at the inter-state migration patterns of new industrial PhDs for states arranged by region by examining the ability of states to retain their own PhDs and import PhDs from other states.[11] Several notable stories arise. Pacific states are all 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 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 contributes to this finding.

[11] 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.

New England and Middle Atlantic states train approximately the same number of PhDs that they hire. However, if it were not for New Jersey, and to a much smaller extent Connecticut, 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 but a quarter of those trained. Indiana PhDs are the most likely to find employment in other states. Of the 376 new industrial PhDs trained in Indiana, 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 skilled 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 metropolitan area 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.[12] 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

[12] 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.

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 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 represent the top five metropolitan areas, both in terms of destination *and* in terms of production of industrial placements. Slightly over one in four of all new S&E PhDs headed to industry were trained in one of these five metropolitan areas, while approximately three out of eight were headed to one of these five metropolitan areas.

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).[13]

Table 3 also shows that striking disparity exists in the ability of metropolitan areas to retain new industrial placements. The mean stay rate for a metropolitan area is 34.1%. 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 amenities, access to venture capital, etc., are present in cities like San Jose, and lacking in cities like Urbana-Champaign.[14]

While the universities like Illinois-Urbana/Champaign, Purdue and Pennsylvania State may appear poor investments 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.

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[13] Patent counts are less highly skewed than SBIR awards; only 33% of all utility patents were awarded in a top five metropolitan area while 50% of all firms awarded an SBIR phase II award were located in one of the top five metropolitan areas,.

[14] 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.

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.

Section V: Empirical Results

In order to investigate specific factors affecting the mobility of new PhDs working in industry, we estimate several equations, using three definitions of mobility. 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 CMSA; that in Equation 3 is whether or not the PhD stays in the same PMSA. 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. In all three equations, the decision to stay is coded as a one; the decision to leave is coded as a 0. All three equations are estimated using a logit model. Equation 4, by contrast, uses OLS to estimate the actual distance that a new PhD moves to take a position outside the PMSA.[15] The equation is estimated only for movers and excludes variables measuring local attributes.[16] Due to heteroscedasticity, we compute robust standard errors.

Table 5 presents the definitions, means, and standard deviations for all variables included in the regressions. Table 6 provides the coefficients and z or t-statistics for the four equations. Table 7 reports the marginal effects of a change in an independent variable, evaluated at the mean. For the logit equations, and 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. In the case of distance, the marginal effects reported in Table 7 take into consideration how the independent variable affects the probability that the individual will move as well as the distance traveled.[17] All PhDs who did not report their postdoctoral state or age are excluded from Equation (1); PhDs whose doctoral institution does not lie in a U.S. CMSA as well as those who did not report a readable city name or age are excluded from Equation 2. Similarly, those whose

[15] To calculate the distance in miles between the city of training and city of employment for each PhD we first gathered the latitude and longitude coordinates of the institution where the PhD was trained and, for those who reported a legible city name in the U.S., where they were employed. After converting the coordinate measures from degrees to radians, we multiplied the number of degrees per radian by the number of miles per degree on a sphere the size of the earth.

[16] In earlier work we used a heckit approach, estimating the probability that the scientist leaves the PMSA to compute an inverse Mills ratio for inclusion in (4). The probit included local PMSA variables excluded from the OLS equation. We find the coefficient on the inverse Mills ratio to be insignificant and reject the hypothesis that the errors between the two equations are correlated.

[17] The formula for the marginal effect of a variable x_k on expected actual distance traveled is defined as, where y is distance, and x_k is the relevant independent variable: $\frac{\partial y}{\partial x_k} = \frac{\partial[\Pr(y>0) * E(y \mid y>0)]}{\partial x_k}$

doctoral institution does not lie in a PMSA are excluded from (3). Equation (4) is further restricted to those having employment plans in the U.S.

Personal characteristics affecting the present value of moving are generally found to be significant at the 5% level or better. An increase in age increases the likelihood that a PhD will stay in the state or metropolitan area of training, consistent with the decrease in the expected stream of future benefits associated with moving that accompanies age. The presence of a spouse increases the probability that the new PhD remains local or stays in the state. Among those who choose to leave, being married also decreases the distance moved. The decision to move is not significantly related to the presence of children, however. Nor is it related to being a single parent.

Very 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 whites are more likely to stay in the state and in the same PMSA. 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. This is not simply because they leave the country. When we restrict the analysis to include only those staying in the U.S. the temporary resident variable remains significant in equations 2 and 3. It may reflect that temporary residents have fewer personal reasons to keep them in the local or state area, as well as the presence of a broader network within the United States. The effect is fairly substantial. Other things being equal, temporary residents are between 7 and 10% more likely to leave the state or MSA area than are citizens.

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 MSA. The marginal effects are not inconsequential. Other things being equal, "stayers" are about 9% more likely to take an industrial position in the state and 6 to 7% more likely to take a position in the city of training, depending upon whether the city is measured at the primary or consolidated level. At the state level we find that individuals who receive their PhD and college degree in the state in which they graduated from high school are even more likely to remain in the state than are those who moved to the state to get a college degree and stayed on to receive their PhD. Moreover, if these individuals do move, they move a shorter distance. The policy implication is clear: accepting PhD students from within the 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 investment in in-state tuition subsidies.

Variables that reflect wider access to networks are generally significant and with the expected sign. Individuals who held fellowships the last year in graduate school, for example, move farther. PhDs from private institutions are more likely to leave the CMSA and move farther when they do. This is consistent with the notion that private institutions through their alumni base have a wider network than do public institutions. Doctorates from a top 110 institution are more likely to leave their metropolitan areas, suggesting that they have a larger employment choice set or that they are more sought after by employers than are doctorates from lower tier-institutions. Individuals trained at top ten programs as rated by the NRC also are more likely to move, although the effect is field dependent as well as dependent on the measure of mobility.[18] In seven of the twelve fields studied, individuals trained at a top ten program are significantly more likely to leave their state than are individuals not trained in a top ten program in their field. And the effects can be quite strong. For example, mathematicians trained at a top math program are approximately 16% more likely to leave the state than are those trained at a non-top ten program. Computer scientists coming from a top program are about 8% more likely to leave the state of training than are those from lower ranked programs as are chemists coming from top programs. Some of these affect distance traveled, as well. Those from top chemistry programs move about 250 miles farther than those who do not come from a top chemistry program. Those from top computer science programs move about 220 miles farther than those from lower-rated departments if they leave the PMSA of training.

Networks, of course, are a two-way proposition. The likelihood of working for a firm not only depends upon the extent of a student's network but also on the network that the hiring firm establishes. We would expect larger firms to be able to recruit the highly skilled from farther distances, whereas smaller firms look to the local labor supply for new hires. Our database allows us to determine whether or not the new PhD is hired by a

[18] A top institution in a given field is defined as one ranked in the top ten based on the National Research Council's 1993 ranking of scholarly quality for all fields except agriculture and medicine. A top institution in these two fields is defined as being among the top ten institutions for federally funded R&D expenditures in the given field. For our fields that are more broadly defined than the NRC program definitions, such as biology, our rankings are based on the mean of all NRC rated programs at an institution that fall under our field definition.

top 200 R&D firm or a subsidiary of a top 200 firm.[19] The results are unequivocal. Individuals hired by top R&D firms or a subsidiary are considerably more likely to leave their state and city of training and if they move they move considerably farther. For example, evaluated at the means, the probability that a top 200 R&D job recipient will stay in state is 11% lower than it is for someone not working for a top 200 firm and it is 10% lower for the PMSA; 8% lower for the CMSA. Moreover, individuals who leave the PMSA and work for a top 200 firm (or subsidiary) take jobs that are 110 miles farther away than are positions in firms that are less R&D intensive.

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 generally support this hypothesis. We find that those working full or part time are more likely to stay in the state and in the primary metropolitan area.

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 were returning to a previous employer are much more likely to stay in state.[20]

Student debt level affects mobility--but not in the way hypothesized. Instead, we find that those with no debt are more likely to stay in state than are those with debt. This counter intuitive result may indicate that students who assumed debt engage in more search activity than do those with no debt, motivated to find a highly remunerative

[19]To determine whether the new PhD was hired by a top 200 R&D firm, we compared a list of the top 200 firms, ranked in terms of money spent on R&D in 1999, and all subsidiaries of these firms, with the firm name each doctorate reported on their SED. The reported firm names from the SED have only been available in verbatim form since 1997. Of the 10,932 doctorates with definite plans in industry between 1997 and 1999, we found that 4,178 had definite plans to work for a top 200 R&D firm.

[20] A doctorate need not remain local, or even in the 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.

position. The absence of debt may also reflect that the pre-doctoral employer paid for schooling with the understanding that the student would return after matriculation. To tease out this effect we interact the "return" variable with the "no debt" variable. We find the interacted variable to be significant and positive in the in-state and in both metropolitan equations, indicating that returning to pre-doctoral employment with no debt enhances the probability that one stays in the state or in the city. We also find that those who are returning with no debt move a shorter distance. At the margin, returning with no debt increases the probability of staying by about 8%.

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. We include measures of innovation in order to proxy the opportunities for R&D industrial employment at the local level; we use per capita income and an education measure of the population as proxies for the desirability of the area. 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.[21] At the CMSA level, patent counts are used as well as the number of industrial labs. In the PMSA equations we substitute the Milken index. 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 R&D labs in

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[21] 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.

the city as well as the number of utility patents granted in the city. At the PMSA level, it is positively related to the Milken Index.[22] At the state level, we find that individuals are more likely to stay if the state has a high level of industrial R&D activity. Somewhat surprisingly, patents are not significant in the state equation and individuals are more likely to relocate outside the state if they come from a state that has large expenditures on academic research. While the latter result appears counter intuitive, it may reflect the quality of academic training and relate to the wider set of job opportunities available to those trained in top programs.

New PhDs are more likely to stay in their state, CMSA or PMSA of training the higher the per capita income in the area. Somewhat surprisingly, the same is not true of the education variable. While the educational level has a positive effect on the stay rate at the state level, at the metropolitan area it is negative and significant.

Section VI: Discussion and Conclusion

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

[22] 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 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.

industry will remain in the same state or metropolitan area. We also examine factors related to distance between a new PhD's university of training and employer.

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 four remain in the same CMSA; 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 area 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 analysis is consistent with other studies of innovation that find a high concentration of innovative activity in certain cities. Specifically, metropolitan areas on the West Coast and in the Northeast appear to have a huge advantage in retaining as well as attracting industrial placements, especially compared to the North Central.

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

What types of programs are associated with retention? First, graduates from certain fields are especially mobile, both at the state and at the MSA level: most notably agriculture, chemistry, economics and the earth sciences. Physics programs produce graduates who are more likely to stay. Quality matters: top-rated PhD programs are often the ones that are most likely to produce graduates who leave the area. Graduates from private institutions are also more likely to find industrial employment outside the metropolitan area of training.

The type of job the individual takes clearly is related to remaining local as well as to the distance traveled. Those taking positions with a top 200 R&D firm (or its subsidiary) are more likely to leave their area of training than are those who take positions with lower-ranked R&D firms. Moreover, they relocate further from the university of training. Those who return to a position they had prior to going to graduate school are more likely to stay.

Not surprisingly, and consistent with a wide body of research on innovation, we find that local areas are more likely to capture locally trained talent if the area is high on measures of innovation such as patent counts and R&D expenditures. Graduates are also more likely to stay in urban areas boasting a higher per capita income.

Our results are consistent with those found by Audretsch and Stephan (1996) concerning the role that proximity plays in knowledge transfer when the mechanism of transfer is embodied in a scientist or engineer. To wit: proximity matters but it does not matter that much. There is a distinction, however, between Audretsch and Stephan's work and this work in the sense that Audretsch and Stephan study faculty ties with firms; here we study recent graduates' ties with firms. The distinction is important. Investing in faculty who establish ties with new firms out of the area while continuing to work at the university is different than educating students who leave the area to take a position with a firm.

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 Ph.D. 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 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 overwhelming 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.

We do not address several questions that are of interest to policy makers and researchers alike. Future work will address certain of these issues, using more appropriate econometric techniques.[23] Two issues are of specific interest: (1) the degree to which amenities affect the location decision and (2) the degree to which placements reflect established networks between faculty and firms.

Florida reports from focus groups with knowledge workers (1999, p. 71) that "They (knowledge workers) want to work in progressive environments, frequent upscale shops and cafes, enjoy museums and fine arts and outdoor activities, send their children to superior schools, and run into people at all these places from other advanced research labs and cutting-edge companies in their neighborhoods. . . Moreover, young graduates know they will probably change employers as many as three times in ten years, and they will not move to an area where they do not feel there are enough quality employers to provide these opportunities." In future work we hope to be able to include amenities in the analysis.

We also are interested in analyzing the role that formal networks play in location decisions. Co-authorship patterns provide one such avenue. In subsequent work we will examine the degree to which co-authorship patterns between university faculty and

[23] We are especially interested in modeling spatial effects.

scientists in firms influence the location decision. We are also interested in examining whether firms are more likely to hire scientists and engineers from institutions that are heavily cited in both the firm's patents and publications.

The implications drawn from this study are somewhat restricted due to the limited scope of the data. 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 Ph.D.s 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 Ph.D.s, the conclusions might differ substantially.

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Table 1
Firm Placements of New S&E Ph.D.s: 1997-1999

Field	Percent of All Ph.D.s Awarded that Identified a Firm	Percent In Field of Ph.D.s that Identified a Firm
All S&E fields	14.5%	100% (n=10,932)
All Engineering	30.7%	49.1% (n=5,364)
Agriculture	9.0%	2.8% (n=308)
Astronomy	7.8%	0.4% (n=44)
Biology	3.8%	5.6% (n=609)
Chemistry	18.7%	11.1% (n=1,216)
Computer Science	28.4%	7.0% (n=762)
Earth Science	12.3%	2.3% (n=252)
Economics	11.8%	3.2% (n=349)
Math	12.5%	4.4% (n=477)
Medicine	5.0%	4.0% (n=435)
Physics	16.1%	6.0% (n=654)
Psychology	6.7%	4.2% (n=462)

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.

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.

Table 4:

Percent of Firm Placements Staying In State and CMSA 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%
Economics	27.0%	26.6%
Math	35.0%	29.4%
Medicine	46.0%	35.2%
Physics	45.0%	35.0%
Psychology	50.0%	39.4%
All Fields	36.7%	27.3%

TABLE 5:
Variable Definitions and Descriptive Statistics

Dependent Variables	*Definition*	*Mean* (Std Dev)*	*Same State Equation*	*Same CMSA Equation*	*Same PMSA Equation*	*Distance OLS Equation*
SameSTATE	Dummy variable indicating whether or not an individual has definite plans to remain in the same state in which they earned their Ph.D.	0.367 (0.482)	XX			
sameCMSA	Dummy variable indicating whether or not an individual has definite plans to remain in the same CMSA in which they earned their Ph.D.	0.273 (0.445)		XX		
samePMSA	Dummy variable indicating whether or not an individual has definite plans to remain in the same PMSA in which they earned their Ph.D.	0.209 (0.4064)			XX	
Distance| samePMSA=0	Distance in miles between the individual's Ph.D. institution and the planned city of employment for Ph.D.s that leave their PMSA	835.438 (806.048)				XX
Independent Variables	*Definition*					
age	Age of the individual at the time of Ph.D.	32.520 (5.043)	X	X	X	X
agesq	Age of the individual squared	1083.00 (373.939)	X	X	X	X
male	Dummy variable indicating whether or not an individual is male	0.798 (0.402)	X	X	X	X
white	Dummy variable indicating whether or not an individual is white	0.555 (0.497)	X	X	X	X
asian	Dummy variable indicating whether or not an individual is Asian or pacific islander	0.378 (0.485)	X	X	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	X	X
tempers	Dummy variable indicating whether or not an individual is a temporary resident in the U.S.	0.333 (0.471)	X	X	X	X
married	Dummy variable indicating whether or not an individual is married	0.613 (0.487)	X	X	X	X
wchild	Dummy variable indicating whether or not an individual is married with at least one child	0.245 (0.430)	X	X	X	X
singlepar	Dummy variable indicating whether or not an individual is not married with at least one child	0.030 (0.170)	X	X	X	X
samece_phd	Dummy variable indicating whether or not an individual earned their Ph.D. in the same state they went to college	0.182 (0.386)	X	X	X	X
samehs_phd	Dummy variable indicating whether or not an individual earned went to high school, college and earned in their Ph.D. in the same state	0.129 (0.336)	X	X	X	X
samebirth_phd	Dummy variable indicating whether or not an individual was born, went to high school, college, and earned in their Ph.D. in the same state	0.085 (0.279)	X	X	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	X	X
nodebt	Dummy variable indicating whether or not an individual had a debt of $0 at the time of degree	0.594 (0.491)	X	X	X	X

retnodebt	Dummy variable indicating whether or not an individual was returning to their previous employer and had zero debt at the time of degree	.1287 (.3349)	X	X	X	X
somedebt	Dummy variable indicating whether or not an individual had a debt between $1 and $20,000 at the time of degree	0.281 (0.449)	X	X	X	X
preftemp	Dummy variable indicating whether or not an individual was full-time employed one year prior to Ph.D.	0.325 (0.468)	X	X	X	X
preptemp	Dummy variable indicating whether or not an individual was part-time employed one year prior to Ph.D.	0.066 (0.248)	X	X	X	X
prefellow	Dummy variable indicating whether or not an individual held a fellowship one year prior to Ph.D.	0.567 (0.496)	X	X	X	X
preunemp_other	Dummy variable indicating whether or not an individual was anything other than full, part time employed or held a fellowship one year prior to Ph.D.	0.035 (0.183)	X	X	X	X
samehs_phd	Dummy variable indicating whether or not an individual earned went to high school, college and earned in their Ph.D. in the same state	0.129 (0.336)	X	X	X	X
astr	Dummy variable indicating whether or not an individual's field of training was astronomy	0.004 (0.063)	X	X	X	X
agri	Dummy variable indicating whether or not an individual's field of training was in agriculture	0.028 (0.165)	X	X	X	X
alleng	Dummy variable indicating whether or not an individual's field of training was engineering	0.491 (0.500)	X	X	X	X
biol	Dummy variable indicating whether or not an individual's field of training was biology	0.056 (0.229)	X	X	X	X
chem	Dummy variable indicating whether or not an individual's field of training was chemistry	0.111 (0.314)	X	X	X	X
comp	Dummy variable indicating whether or not an individual's field of training was computer science	0.070 (0.255)	X	X	X	X
earth	Dummy variable indicating whether or not an individual's field of training was earth science	0.023 (0.150)	X	X	X	X
econ	Dummy variable indicating whether or not an individual's field of training was economics	0.032 (0.176)	X	X	X	X
math	Dummy variable indicating whether or not an individual's field of training was mathematics	0.044 (0.204)	X	X	X	X
medi	Dummy variable indicating whether or not an individual's field of training was medicine	0.040 (0.195)	X	X	X	X
phys	Dummy variable indicating whether or not an individual's field of training was physics	0.060 (0.237)	X	X	X	X
psyc	Dummy variable indicating whether or not an individual's field of training was psychology	0.042 (0.201)	X	X	X	X
topsastr	Dummy variable indicating whether or not an individual's Ph.D. field was astronomy and their Ph.D. institution was ranked in the top ten for astronomy	0.001 (0.037)	X	X	X	X
topsagri	Dummy variable indicating whether or not an individual's Ph.D. field was agriculture and their Ph.D. institution was ranked in the top ten for agriculture	0.006 (0.080)	X	X	X	X
topsalleng	Dummy variable indicating whether or not an individual's Ph.D. field was in engineering and their Ph.D. institution was ranked in the top ten for engineering	0.127 (0.333)	X	X	X	X
topsbiol	Dummy variable indicating whether or not an	0.009	X	X	X	X

	individual's Ph.D. field was biology and their Ph.D. institution was ranked in the top ten for biology	(0.096)				
topschem	Dummy variable indicating whether or not an individual's Ph.D. field was chemistry and their Ph.D. institution was ranked in the top ten for chemistry	0.024 (0.154)	X	X	X	X
topscomp	Dummy variable indicating whether or not an individual's Ph.D. field was computer science and their Ph.D. institution was ranked in the top ten for computer science	0.017 (0.129)	X	X	X	X
topsearth	Dummy variable indicating whether or not an individual's Ph.D. field was earth science and their Ph.D. institution was ranked in the top ten for earth science	0.005 (0.069)	X	X	X	X
topsecon	Dummy variable indicating whether or not an individual's Ph.D. field was economics and their Ph.D. institution was ranked in the top ten for economics	0.009 (0.093)	X	X	X	X
topsmath	Dummy variable indicating whether or not an individual's Ph.D. field was mathematics and their Ph.D. institution was ranked in the top ten for mathematics	0.007 (0.084)	X	X	X	X
topsmedi	Dummy variable indicating whether or not an individual's Ph.D. field was medicine and their Ph.D. institution was ranked in the top ten for medicine	0.003 (0.056)	X	X	X	X
topsphys	Dummy variable indicating whether or not an individual's Ph.D. field was physics and their Ph.D. institution was ranked in the top ten for physics	0.014 (0.117)	X	X	X	X
topspsyc	Dummy variable indicating whether or not an individual's Ph.D. field was psychology and their Ph.D. institution was ranked in the top ten for psychology	0.003 (0.056)	X	X	X	X
private	Dummy variable indicating whether or not an individual received their Ph.D. from a private institution	0.324 (0.468)	X	X	X	X
toponeten	Dummy variable indicating whether or not an individual received their Ph.D. from a top 110 institution	0.817 (0.386)	X	X	X	X
top200	Dummy variable indicating whether or not an individual has definite plans to work for a top 200 R&D firm	0.382 (0.486)	X	X	X	X
STpats	Number of patents in thousands granted in the state of the individual's Ph.D. institution between 1997-1999	6.49 (6.66)	X			
STacadrd	Academic R&D expenditures in millions in the state of the individual's Ph.D. 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 Ph.D. 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 Ph.D. institution	75.852 (66.31)	X			
STpop	Population in hundred thousands in the state of the individual's Ph.D. institution in 2000	129.696 (99.816)	X			
STperhe	Percent of the population age 25+ in the state of the individual's Ph.D. 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	22.953	X			

	individual’s Ph.D. institution in 1994	(2.570)				
cmsapats	Number of patents in hundreds granted in the CMSA of the individual's Ph.D. institution between 1997-199	8.28 (8.71)		X		
cmsalabs	Number of R&D labs in the CMSA of the individual's Ph.D. institution in 1995	329.83 (387.87)		X		
cmsasize	Geographic size in thousands of square miles of the CMSA of the individual's Ph.D. institution	6.525 (7.165)		X		
cmsapop	Population in hundred thousands in the CMSA of the individual's Ph.D. institution in 2000	46.161 (54.41		X		
cmsaperhe	Percent of the population age 25+ in the CMSA of the individual’s Ph.D. institution with a Bachelor’s degree or higher in 1999	30.78 (5.78)		X		
cmsapcinc	Per Capita income in thousand in the CMSA of the individual’s Ph.D. institution in 1999	23.248 (3.441)		X		
pmsapats	Number of patents in hundreds granted in the PMSA of the individual's Ph.D. institution between 1997-199	8.17 (8.68)		X		
milkenind	Milken Index in the PMSA of the individual’s Ph.D. institution in 202	1.110 (0.711)			X	
pmsasize	Geographic size in thousands of square miles of the PMSA of the individual's Ph.D. institution	2.464 (2.116)			X	
pmsapop	Population in hundred thousands in the PMSA of the individual's Ph.D. institution in 2000	25.22 (26.54)			X	
pmsaperhe	Percent of the population age 25+ in the PMSA of the individual’s Ph.D. 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 Ph.D. institution in 1999	31.62 (5.863)			X	

Table 6:
Empirical Results

	Dependent Variable = SameSTATE N=10,817		Dependent Variable = SameCMSA N=9,830		Dependent Variable = SamePMSA N=9,605		Dependent Variable = Distance|SamePMSA=0 N=6595	
Variable	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat	Coefficient	t-stat
Intercept	-4.799***	-6.14	-6.715***	-7.74	-4.957***	-5.81	1001.2***	3.18
age	0.077**	2.05	0.097**	2.33	0.070*	1.68	-21.7	-1.30
agesq	-0.0006	-1.24	-0.0008	-1.48	-0.0005	-0.92	0.289	1.29
male	-0.086	-1.43	-0.068	-1.02	-0.019	-0.26	54.1**	2.12
white	0.227**	2.37	0.101	0.95	0.255**	2.25	47.5	1.19
asian	0.073	0.71	-0.109	-0.96	-0.044	-0.35	32.2	0.73
permres	0.129	1.51	-0.060	-0.63	-0.048	-0.48	1.3	0.03
tempres	-0.336***	-4.88	-0.490***	-6.37	-0.476***	-5.75	41.3	1.30
married	0.115**	2.13	0.114*	1.90	0.124*	1.91	-53.0**	-2.29
wchild	0.017	0.27	-0.006	-0.09	0.017	0.23	-44.9*	-1.65
singlepar	-0.083	-0.60	-0.204	-1.32	-0.047	-0.29	-40.5	-0.68
samece_phd	0.423***	4.27	0.340***	3.12	0.345***	3.10	-72.8	-1.54
samehs_phd	0.345**	2.47	0.121	0.80	-0.149	-0.96	-156.4**	-2.49
samebirt_phd	0.074	0.59	0.058	0.43	0.245*	1.74	71.4	1.32
return	0.225**	2.30	0.130	1.18	0.098	0.85	-73.2	-1.59
nodebt	0.135*	1.76	0.122	1.41	0.110	1.2	-40.1	-1.23
retnodebt	0.347***	3.04	0.393***	3.11	0.404***	3.09	-98.1*	-1.82
somedebt	0.011	0.14	-0.051	-0.59	-0.049	-0.53	-22.4	-0.68
preftemp	0.475***	3.95	0.330**	2.52	0.399***	2.76	57.5	1.02
preptemp	0.908***	6.47	0.732***	4.84	0.880***	5.40	16.7	0.26
prefellow	0.097	0.83	-0.007	-0.06	0.123	0.87	150.7***	2.80
astr	0.637	1.46	0.892**	1.98	0.308	0.65	474.1*	1.65
agri	-0.422**	-2.26	-0.851***	-3.22	-0.516*	-1.84	-162.2**	-2.44
alleng	-0.038	-0.35	0.107	0.87	0.229*	1.78	27.9	0.57
chem	-0.374***	-2.92	-0.311**	-2.11	-0.122	-0.78	-83.6	-1.54
comp	-0.126	-0.90	-0.116	-0.74	0.049	0.30	186.2***	2.83
earth	-0.564***	-2.77	-0.638**	-2.54	-0.703**	-2.54	-43.1	-0.65
econ	-0.607***	-3.36	-0.394**	-1.96	-0.552**	-2.52	-98.7	-1.29
math	0.042	0.27	0.372**	2.17	0.518***	2.90	-76.0	-1.20
medi	-0.166	-1.07	-0.117	-0.68	-0.068	-0.38	-55.6	-0.85
phys	0.289**	2.05	0.524***	3.35	0.619***	3.79	101.4	1.41
psyc	-0.043	-0.28	0.127	0.76	0.279	1.64	58.1	0.85
topsastr	-0.023	-0.03	-0.039	-0.05	0.379	0.50	-575.1	-1.42
topsagri	-0.600*	-1.74	0.005	0.01	-0.028	-0.05	118.6	1.17
topsalleng	-0.209***	-2.63	-0.135	-1.58	-0.408***	-4.2	52.7	1.61
topsbiol	0.167	0.67	0.475*	1.93	0.638**	2.39	86.4	0.42
topschem	-0.414**	-2.37	-0.135	-0.71	-0.298	-1.4	242.7***	3.26
topscomp	-0.347*	-1.70	0.311	1.42	0.159	0.69	323.3***	3.50
topseart	-0.769**	-2.08	-0.208	-0.52	-0.424	-0.92	260.6	1.56
topsecon	-0.529*	-1.70	-0.502*	-1.71	-0.337	-0.96	56.2	0.43

topsmath	-0.760**	-2.52	-0.545*	-1.83	-0.579**	-1.81	-39.5	-0.29
topsmedi	-0.189	-0.45	-0.376	-0.90	-0.722	-1.57	179.1	0.94
topsphys	0.010	0.05	-0.056	-0.25	-0.433**	-1.80	-179.5*	-1.65
topspsyc	-0.435	-1.10	-0.327	-0.79	-0.303	-0.69	-20.2	-0.11
private	0.075	1.33	-0.280***	-4.17	-0.044	-0.63	78.1***	3.20
toponeten	-0.084	-1.35	-0.269***	-3.68	-0.178**	-2.37	36.4	1.30
top200	-0.494***	-10.1	-0.562***	-10.19	-0.573***	-9.65	111.4***	5.46
STpats	-0.0066	-1.28	n/a	n/a	n/a	n/a	n/a	n/a
STacadrd	-0.04488	-1.31	n/a	n/a	n/a	n/a	n/a	n/a
STindrd	0.0303***	4.24	n/a	n/a	n/a	n/a	n/a	n/a
STsize	0.00563***	8.31	n/a	n/a	n/a	n/a	n/a	n/a
STpop	0.0003	.210	n/a	n/a	n/a	n/a	n/a	n/a
STperhe	0.0187*	1.78	n/a	n/a	n/a	n/a	n/a	n/a
STpcinc	0.0379**	2.03	n/a	n/a	n/a	n/a	n/a	n/a
cmsapats	n/a	n/a	0.0564***	11.70	n/a	n/a	n/a	n/a
cmsalabs	n/a	n/a	0.0005***	4.41	n/a	n/a	n/a	n/a
cmsasize	n/a	n/a	0.0415***	8.92	n/a	n/a	n/a	n/a
cmsapop	n/a	n/a	-0.0041***	-5.04	n/a	n/a	n/a	n/a
cmsaperhe	n/a	n/a	-0.0181***	-3.12	n/a	n/a	n/a	n/a
cmsapcinc	n/a	n/a	0.1506***	10.76	n/a	n/a	n/a	n/a
pmsapats	n/a	n/a	n/a	n/a	0.0181***	3.10	n/a	n/a
milkenind	n/a	n/a	n/a	n/a	0.4748***	8.10	n/a	n/a
pmsapop	n/a	n/a	n/a	n/a	0.0139***	9.46	n/a	n/a
pmsasize	n/a	n/a	n/a	n/a	0.0569***	4.44	n/a	n/a
pmsaperhe	n/a	n/a	n/a	n/a	-0.0193***	-3.46	n/a	n/a
pmsapcinc	n/a	n/a	n/a	n/a	0.0325***	4.11	n/a	n/a
Log likelihood ratio/ r-square	2216.49		2298.87		1596.16		.059	

*** Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

Table 7:
Marginal Effects

	Dependent Variable = SameSTATE	Dependent Variable = SameCMSA	Dependent Variable = SamePMSA	Dependent Variable = Distance
age	0.0172	0.01788	0.0105	-9.235
agesq	n/a	n/a	n/a	0.2506
male	-0.0196	-0.0130	-0.003	41.641
white	0.0509	0.0195	0.039	35.473
asian	0.0160	-0.0201	-0.006	24.827
permres	0.0307	-0.0121	-0.008	1.024
tempres	-0.0747	-0.0895	-0.069	32.688
married	0.0261	0.0214	0.019	-40.099
wchild	0.0140	-0.0012	0.021	-34.240
singlepa	-0.0181	-0.0369	-0.007	-31.106
samece_phd	0.0870	0.0674	0.0564	-55.225
samehs_phd	0.0855	0.0263	-0.0258	-120.560
samebirth_phd	0.0186	0.0130	0.0082	54.792
return	0.0521	0.0251	0.015	-56.047
nodebt	0.0305	0.0230	0.017	-30.392
retnodeb	0.0828	0.0799	0.085	-74.552
somedebt	0.0023	-0.0097	-0.007	-17.254
preftemp	0.1066	0.0726	0.059	43.197
preptemp	0.2133	0.1522	0.150	12.705
prefellow	0.0204	-0.0013	0.017	114.184
astr	0.1578	0.2022	0.061	363.954
agri	-0.0997	-0.1265	-0.054	-124.777
alleng	-0.0093	0.0133	0.047	20.737
chem	-0.0888	-0.0462	-0.007	-64.250
comp	-0.0307	-0.0171	0.018	142.761
earth	-0.1305	-0.0971	-0.072	-33.178
econ	-0.1397	-0.0627	-0.057	-75.994
math	0.0103	0.0762	0.100	-58.014
medi	-0.0404	-0.0180	-0.009	-42.663
phys	0.0720	0.1070	0.121	77.160
psyc	-0.0105	0.0266	0.056	44.511
topsastr	-0.0058	-0.0096	0.0740	-441.496
topsagri	-0.0721	0.0006	-0.0028	91.060
topsalleng	-0.0084	-0.0262	-0.0614	40.974
topsbiol	0.0403	0.1006	0.0892	66.284
topschem	-0.0798	-0.0209	-0.0367	186.645
topscomp	-0.0753	0.0606	0.0256	248.120
topseart	-0.1215	-0.0391	-0.0318	200.099
topsecon	-0.0874	-0.0655	-0.0296	43.134
topsmath	-0.1616	-0.1088	-0.0983	-30.350
topsmedi	-0.0415	-0.0608	-0.0798	137.595
topsphys	0.0026	-0.0129	-0.0807	-138.011
topspsyc	-0.0955	-0.0613	-0.0486	-15.521

private	0.0168	-0.0520	-0.007	60.113
toponete	-0.0190	-0.0533	-0.028	28.842
top200	-0.1083	-0.1033	-0.084	89.695
STpats	-0.0015	n/a	n/a	n/a
STacadrd	-0.0102	n/a	n/a	n/a
STindrd	0.0069	n/a	n/a	n/a
STsize	0.0013	n/a	n/a	n/a
STpop	0.0001	n/a	n/a	n/a
STperhe	0.0042	n/a	n/a	n/a
STpcinc	0.0086	n/a	n/a	n/a
cmsapats	n/a	0.0107	n/a	n/a
cmsalabs	n/a	0.0001	n/a	n/a
cmsasize	n/a	0.0079	n/a	n/a
cmsapop	n/a	-0.0008	n/a	n/a
cmsaperhe	n/a	-0.0034	n/a	n/a
cmsapcinc	n/a	0.0286	n/a	n/a
pmsapats	n/a	n/a	0.0034	n/a
milkenin	n/a	n/a	0.0894	n/a
pmsasize	n/a	n/a	0.0107	n/a
pmsapop	n/a	n/a	0.0026	n/a
pmsaperhe	n/a	n/a	-0.0036	n/a
pmsapcinc	n/a	n/a	0.0061	n/a