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Empirical Analysis of Career Transitions of Sciences and Engineering Doctorates in the US

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Empirical Analysis of Career Transitions of Sciences and Engineering Doctorates in the US

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Abstract

This paper studies career mobility of white male doctorates in natural sciences and engineering using the Survey of Doctorate Recipients (1973-2001). The paper focuses on two issues. First, it assesses the relevance of doctoral careers to sciences and engineering (S&E) in general, and research and development in particular. Second, it evaluates participation rates and mobility patterns of doctorates in careers of different types. To analyze how various factors affect mobility, a transition model with competing risks is specified and estimated. The paper finds that only half of doctorates have careers in R&D, and another 8% work in occupations outside the scope of S&E. Employment choices vary throughout a career. Mobility both within- and out of S&E is especially high during the first 16 years on the job. The effects of individual and job characteristics, research productivity, and labor market conditions on transitions are also assessed.

Keywords: *Occupational transitions; duration analysis; competing risks; science and technology workforce; high-skilled labor.*

JEL Classification Codes: C41, J24, J44.

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1 Introduction

This paper studies career choices and mobility patterns of white male doctorates in natural sciences and engineering (S&E). While it may be believed that a doctorate's career is typically associated with research and development, there exists anecdotal evidence that a large fraction of S&E doctorates find employment opportunities in such non-traditional for scientists areas as financial-, accounting- and other business services, non-technical consulting, and law. The consequences of these career changes depend on their nature and factors that affect it. This raises the following questions: What do we know about career choices of S&E doctorates? Who chooses to make a career change, when, and why? How does outward mobility from S&E compares with that between S&E-related jobs?

The first objective of the paper is to assess relevance of the doctoral careers to S&E in general, and to R&D in particular. The second goal is to compare participation rates and mobility patterns of doctorates in careers of different types. The third objective is to evaluate how various personal- and job characteristics, research productivity, and labor market conditions affect mobility within- and out of S&E. An econometric model of transitions with competing risks is specified and estimated using the Survey of Doctorate Recipients (SDR) collected by the NSF during 1973-2001. This longitudinal data set is unique because of its large representative sample of professionals whose share in the labor force is small. As a data source on careers, the SDR is rich in employment characteristics specific to S&E.

The first main finding of the paper is that only 57% of doctorates in the sample worked in R&D. Another 35% worked in occupations that involve *application* rather than *creation* of new knowledge and products. Finally, 8% of doctorates worked outside S&E in such sectors as financial- and other business services. This finding contradicts the common perception that S&E doctorates have very narrowly specialized skills unsuitable outside academic research.

The second finding is that career choices vary within a career. Doctorates tend to begin their careers in R&D (72%) but only half of them are still in R&D thirty years later. Some of those who leave go to applied jobs (80%) and others leave S&E for good (20%). The transitions within- and out of S&E differ in their timing and patterns. The only common feature is their high frequency within the first 16 years of job-specific tenure. Switchers from R&D to application are more likely to be tenured academics, while returns to R&D from application are conditional on active publishing and patenting activity. Finally, those who leave S&E are more likely to do so from the private sector. They are more likely to be graduates from highly ranked institutions, have a pre-PhD degree in non-S&E fields. Finally those who leave R&D for non-S&E tend to have higher number of postdoctoral appointments prior to the exit.

Finally, analysis of the macroeconomic conditions at the time of the transition shows that high R&D expenditures relative to the GDP decreases mobility of all types. Growth of the R&D expenditures can be thought of as an increase in demand for R&D labor. Therefore, it is not surprising that increase in demand for labor decreases the turnover of labor. High enrollment rates in S&E programs used to indicate increase in demand for faculty are found to increase mobility into both R&D-related and applied jobs. These results suggest that the S&E labor supply is sensitive to the changes in the labor market conditions.

This paper is closely related, first of all, to the studies of the S&E labor force, considered in more detail in the next section. Secondly, it belongs to the literature on applications of the duration analysis to problems with multiple states and competing risks. The first contribution of the paper is its assessment of retention rates in R&D and factors affecting it. The second is its analysis of "career changes" of S&E doctorates.

The paper is organized is follows. Section 2 describes the relevant literature. Section 3 describes the data and describes empirical patterns on career choices and mobility of doctorates. Section 4 outlines a competing risks transition model used to evaluate four transitions among three job-types: between R&D and applied jobs, and between S&E- and non-S&E type jobs. Finally, Section 5 contains discussion of the estimation results and discussion of further research.

2 Literature

Existing literature on doctoral employment focuses on career paths traditional for this group of professionals such as R&D or teaching jobs in academia, government or private sector. Mobility out of R&D and complete career changes of doctorates considered in this paper have not been assessed in the S&E literature before. The studies of the traditional career paths can be grouped into two major strands. The first strand is concerned with employment and mobility *within* a specific sector, such as managerial vs. technical jobs in R&D firms (Ferrall (8), Biddle and Roberts (3)), promotions within academia (Robin (14), Grimes and Register (9)), or mobility between firms (e.g Moen (12), Fallick et al. (7), Almeida and Kogut (1)). The second strand studies mobility *between* R&D sectors, e.g. Zucker and Darby (17), Audretsch and Stephan (2).

Mobility within R&D sectors serves as a vehicle of transferring new ideas through their inventors who most often hold patents on these inventions rather than publish their findings freely in scientific journals. In these cases employing the inventors becomes the only way to access the new developments. On one hand, this type of mobility is a concern since it reduces firms' incentives to invest into human capital. On the other hand, it is beneficial for the firms-recipients. Almeida and Kogut (1) analyze mobility of engineers - patent-holders and patterns of their patent citations in semiconductors industry. They find notable regional differences in knowledge localization, especially in such regions as the Silicone Valley, and the New York Triangle. They explain this phenomenon by existence of a large local market for scientists and engineers in these regions. Their finding about high mobility is supported by Fallick et al. (7) who analyze interfirm transitions in high technology clusters using the CPS data. They discover very high transition rates within computer clusters in California such as the Silicone Valley. The authors explain this phenomenon with such features of the state law as restriction on non-compete agreements. The firms with superior innovations benefit from such mobility because it causes reallocation of human resources towards these firms. The authors show that under certain conditions there is a net benefit of this kind of mobility but for technological reasons it is specific to the computer industry only. Moen (12) considers this issue using the human capital framework. He shows that in the R&D-intensive firms workers are paid much lower wages early in their career. He considers this a payment for acquiring training, for which they are compensated later in their careers. He suggests that all possible externalities of labor mobility are internalized by the market.

The second strand of literature considers mobility between different sectors, e.g. academia or government laboratories and industry (Zucker et al. (18), Zucker and Darby (17), Audretsch and Stephan (2)). The major interest in the latter kind of mobility is explained by possibilities of knowledge diffusion across sectors through reallocation of researchers. Zucker et al. (18) study behavior of the academics moving to the industry. Later Zucker and Darby (17) extend the scope of analysis to all areas of sciences. Both studies estimate a duration model to show that it is the "star" scientists that make the move. The quality of a scientist is determined by the number of primary accession numbers (similar to citations) obtained from the GenBank. Audretsch and Stephan (2) analyzed a similar type of mobility of doctorate biologists - founders of bioscience firms. They also found that the "switchers" are the "star" scientists, who start their own company rather than join a bigger one. This interesting observation proves the prediction of the human capital theory that early in their careers, academic scientists would heavily invest in their knowledge in order to build reputation, and cash it out later, by selling their services to a private firm or by starting their own business.

A slightly different aspect of mobility was considered in an earlier paper, by Biddle and Roberts (3), where the authors model and empirically test one of the career paths of industrial engineers that begins in a technical- and then can be continued in a managerial occupation. A self-selection and job matching framework was used to determine who and why decides to switch to the managerial track and whether to stay on it or not. The key assumption in the paper is that the skills to perform technical and managerial tasks are positively but imperfectly correlated. Therefore, the model predicts that the most productive technical workers would also be more productive as managers, and therefore, they choose to switch to management later in the career. Another prediction of the model was that those who switched the tracks and turned out to be unproductive as managers would backtrack. The authors found empirical support for the first prediction of the model but not the second.

3 Empirical evidence on career choices and transitions

This section describes the data and outlines main facts on occupational choices of the PhDs, relevance of these choices to S&E and R&D, and transition patterns between jobs of different types.

3.1 Data

The stylized fact in this section are derived from the rarely used Survey of Doctorate Recipients (SDR), collected biennially by the NSF since 1973. This longitudinal survey includes only individuals who graduated from the US PhD programs and resided in the US at the time of the survey. In the original 1973 survey, the target population included graduates between 1930 and 1973. With every survey, a fraction of new graduates was added. At the same time, some of the previous respondents are removed from the survey because they reach the age of 76 or for sampling reasons. This way, in 2001 the survey included 40,000 individuals representing 650,000 doctorates under age of 76 residing in the US.

The survey is unique, first of all, because it provides information on the group of professionals, which is small relative to the population. Due to this problem, other data sets (e.g. CPS) would have a very small number of individuals with PhD degrees. Secondly, the data in the SDR is longitudinal, and allows following the individuals as their careers unfold. This is crucial for analysis of transitions and their duration. Finally, the survey asks about academic achievements and other profession-specific information usually unavailable in the general type surveys. There exist several studies of doctorates that used other data sets, primarily collected by the authors, e.g. Mangematin (11), **(author?)** (Gaughan and Robin), Oyer (13), Diamond (6), Grimes and Register (9). These data sets were compiled in most cases from individuals' CVs posted on their web sites. The advantage of this approach is that it allows to construct complete employment histories and have full productivity information not available in the SDR. Unfortunately, I could not follow their example or use one of their data sets because of their small size (few hundred observations at best) and concentration on the academic sector.

The major interest to this study were employment records. They contain information on the employer (e.g. region, sector, size, detailed type of industry), occupation and its relevance to the degree major (NSF taxonomy), primary and secondary activities on the job (including such specific activities as basic and applied research, design, and development), information on professional activity (membership in scientific societies, participation in conferences), as well as scientific productivity variables (publications and patents). Unfortunately, the latter data was collected only in selected years (1983, 1991-2001) and does not include any publications or patents individuals had before graduation. The only variable suitable to serve as a proxy for quality of a researcher that was consistent throughout the entire period was information on the degree-granting institution (institution code, its public or private status, and its Carnegie classification). Another shortcoming of the survey is incompleteness of career histories. Some histories have gaps due to non-response in some years. Other histories are not observed from the beginning because individuals were included in the survey years after they graduated. The questions about employment are concerned with the year preceding the survey, and unlike information on education, is not retrospective. Construction of the employment history from graduation was possible only for the individuals who were followed from the moment of their graduation and provided enough information on their employment.

The sample was limited to white men with PhDs in natural sciences[1] and engineering, who were employed full-time, had no secondary jobs and responded to all job-related questions in at least 3 consecutive surveys. Due to these conditions, the sample size reduced to 15,000 individuals, with characteristics described in the last column of Table 3. Individuals in the sub-sample are on average 45 years of age, most likely to be native citizens (81%), unmarried (53%), with a health or physical science degree (44% and 28% respectively), who graduated from public universities (66%), which is most likely to be a Research I or II institution in the Carnegie classification (88%). They are more likely to work in the academe (47.8%) and have published about 2 research papers around the time of graduation. Finally, the sub-sample consists mostly of the cohorts who graduated between 1975 and 1985.

3.2 Types of careers and assignment principles

I next analyze occupations, primary activities on the job, and employer sector to determine the extent to which careers of scientists are related to R&D. First, I evaluate occupations and their relevance to the R&D. Individuals were asked to choose an occupation from the list that most closely resembles their primary jobs (see the Appendix for the list of major occupational groups). All occupations could be grouped into: a) scientists, b) engineers, c) post-secondary teachers, d)top- and mid-level managers, and e) non-S&E others. Comparison of the occupational choice by major showed that individuals are concentrated mostly in occupations defined as "scientist"

[1]Natural sciences include mathematics and computer sciences, life and health sciences, and physical sciences.

("engineer") or "teacher" in the same discipline as the major of their degree (Table 1), with some minor exceptions, e.g. some mathematicians- or physicists-by-training worked as teachers in engineering or life sciences programs. This finding suggests that for the purposes of my analysis I can consider aggregate occupational groups (say, "postsecondary teacher in S&E" or "scientist") rather than detailed occupations, which gives me 4 occupational groups: scientists and engineers, postsecondary teachers, managers, other non-S&E occupations.

Next, the respondents were asked to report an activity that occupies majority of their time on a typical week at their primary job. The list of activities contained 14 possibilities, which could be grouped into a) R&D activities (basic and applied research, development and design); b) teaching, professional services, software design; c) managerial and administrative activities including marketing, sales, quality control, general management, and d) finance, accounting. Activities in the first group can be thought of "creation" new knowledge and products, while activities in the second group are oriented on "application" of accumulated knowledge and technologies. I tabulate activities by occupation and find that occupations include a mixture of activities, which have various relevance to R&D (Table 2). In addition, since an occupation is self-reported, there are cases where major activities do not agree with the reported occupation. For example, some individuals classify themselves as physicists but their primary activities are reported as accounting and finance, or teachers who report R&D-type activities and no teaching. The latter case can be an example of an academic, who is categorized as a teacher (probably recoded by the NSF) even if she does primarily research as is the case in the top departments. While the former case can be an example of an individual who is a physicist by training employed outside S&E. Therefore, judging about the relevance of the job to R&D cannot be based on the occupation only. Moreover, after studying industry of the employer, it became evident that some individuals report themselves as scientists even if they work in non-S&E industries, such as financial and other business services. Analysis of the activities of these scientists show that they are mostly involved in accounting, finance, or professional services.

Using information on occupations, industry of employment, and primary activities, I divide all occupations into three categories. Two of them belong to the S&E sector. The third type includes jobs unrelated to S&E and is further referred to as a non-S&E type. I distinguish between S&E and non-S&E jobs to pin down the "career change" type of mobility as opposed to other types considered in previous studies. Within S&E, occupations differ in required skills and their prices, depreciation rates, and other features. To reflect this, I further divide them into two groups: R&D- and application-related jobs. The first type includes occupations defined by the NSF taxonomy as scientists (e.g. physicist) and engineers (e.g. mechanical engineer) if individuals indicated R&D as activities that occupy the main time on the job, regardless of the employment sector. Finally, I included certain managerial occupations, which involve R&D activities, supervision of R&D activities, or imply employment in R&D related sectors. The second type, "application of knowledge" or briefly "applied", includes occupations that require mostly application of the accumulated scientific or technical knowledge rather than development of new knowledge. An example would be teaching in S&E fields in both secondary and post-secondary institutions, professional services in S&E (e.g. technical consulting, project evaluations, surveying, etc.), or managerial and sales activities in these areas.

The last category, non-S&E type occupations, include jobs unrelated to S&E. In order to distinguish relevance of the job to S&E I use a different taxonomy than that adopted by the NSF[2]. For example, NSF taxonomy considers all managerial occupations as unrelated to S&E. This way, the head of a university department or a director of a research laboratory would be considered as someone who changed his career. For the purposes of my analysis such a classification would give misleading results because mobility from S&E to non-S&E would include both career advancements (exits due

[2]For a list of NSF categories of occupations see Appendix

to promotions) and career changes. Distinguishing between the two is possible only when managerial occupations are separated by their relevance to S&E. One example of non-S&E jobs would be teaching non-S&E subjects (e.g. in humanities, business[3], law, or arts). The second example would be employment in areas of legislation, business services, such as finance, accounting, non-technical consulting, or marketing and sales of products and services in non-S&E industries (e.g. tourism and hospitality, entertainment, media). Some might argue that business consulting or legislation in high-tech industries or manufacturing requires technical knowledge. I agree with this note but suggest however that technical education for these professions does not require to be at the doctoral level.

3.3 Career choices and empirical transitions

Overall, 56.7% of all doctorates in the sample were employed in R&D-related jobs. Application-type jobs accounted for 35.4% of all employment. The remaining 7.8% worked in non-S&E jobs. These facts contradict a common perception that S&E skills of doctorates are narrowly specialized and find no utilization outside their profession.

The first three columns in Table 3 reports the summary statistics by job-type. The main difference in observed characteristics between the employed in non-S&E fields compared to the rest is their age: they are on average older (48.5 years vs. 45 years-old as sample average) mostly because they join non-S&E later in their career (age at the start of the spell is 7 years later than the average). Differences in other features are not substantial. For example, there is a slightly higher fraction of engineers in these occupations compared to the average. They are more likely to have a degree in business, humanities, or social sciences preceding their PhD, which demonstrates that they have non-S&E skills or have preferences towards non-S&E occupations. Finally, they report the lowest number of papers early in their careers (1.17 vs. 2.014 on average). This might suggest that they were unproductive as

[3]For certain social science majors, especially for economists, business would not be an unrelated area. However, social science doctorates were excluded from the estimation sample.

researchers. Alternatively, they did not focus on research intentionally because they did not plan to work in S&E. Both explanations might indirectly suggest that scientific success is not directly valued outside S&E. Individuals in R&D-related jobs are the youngest (43.7 years-old), have a higher fraction of foreign-born among them than other fields (19%) and more likely to graduate (86.7%) and work (24.3%) in Carnegie Research I and II universities. Conditional on being in academe, they are most likely to hold post-doctorate and other non-tenured positions (48% vs 28% in applied jobs). Finally, they are also the least likely to have degrees in non-S&E fields.

Career choices vary throughout a career. As shown on Figure 1, participation in R&D jobs is high early in the career (75%), while employment outside S&E is very low (3%). However, only 45% of doctorates are still in R&D thirty years after graduation. Employment in applied jobs grows from 25% right after graduation to 42% at the end of the career. Non-S&E jobs account for 10% of all employment by twenty years after graduation and remain stable thereafter. The next section analyzes the transition patterns in more detail to understand their nature.

3.3.1 Mobility patterns

Transitions between different types of jobs can be divided into transitions within S&E vs transitions out of S&E. For 15,000 individuals there were on average 1.73 task-specific spells. Unfortunately, this means that I do not observe any repeated spells of the same type, which makes it impossible to estimate a duration model with dependent risks using the joint distribution of unobserved heterogeneity[4]. The longest observed spells were 28 years-long. However, the number of individuals in long spells was small: less than 100 people in total. Due to this problem, only spells with more than 20 observations were considered, which shortened the longest spell to 18 years.

There are 7 most common career paths in the data: a) uninterrupted employment in R&D (28%), b) uninterrupted employment in applied jobs (22%), c) careers starting

[4]See D'Addio and Rosholm (5) for a discussion of identification problems in this type of models

in R&D and eventually transferring into application (12%), d) career starting in application that eventually ends in R&D (6%), e) employment in R&D with a short intermediate spell in an applied job (5.35%), f) employment in applied job with a short intermediate spell in R&D (3.28%), g) career that begins in either R&D or application and eventually follows by an exit to non-S&E(2.8% and 2% respectively). The remaining 18% have other career patterns, including non-S&E employment.

Table 4 contains average transitions rates. One can notice that R&D-related jobs have slightly higher retention rates compared to those in applied jobs: 0.61 vs 0.58 respectively. In addition, average transition rates to non-S&E are also similar: 0.07 out of R&D compared to 0.08 out of application. The next subsection considers the transition dynamics in more detail.

Reallocations within S&E

Figures 2 and 3 demonstrate transition rates between S&E tasks for different disciplines over time. The horizontal axis depicts task-specific tenure at the time of the transition. The empirical exit rate $e_{ij}(t)$ on the vertical axis is a fraction of individuals who left the job i for the job of the type j after being employed in job i for t years, out of the total number of the employed in the job of type i for t years. There are several interesting observations that are worth noting. First of all, transition rates from R&D to application are non-monotonic: they are stable within the first 10 years of employment, then they fall by half by year 14 and increase thereafter. This type of transition occurs in two "waves": the first one within the first 8 to 10 years in occupation and the second after 14 to 18 years. Notably, the first wave occurs during the time believed to be crucial for building the foundation for reputation and recognition in R&D. The second wave could include established scientists who leave R&D for consulting and similar jobs (Zucker et al. (18), Cater and Lew (4)), which is consistent with predictions of the human capital theory. Transitions are notably high for mathematicians (twice of that in other disciplines), especially within the first 14 years. This might suggest higher competition for R&D positions in mathematics, especially considering that most of these people are employed in academic institutions with tenure requirements, or higher return to experience in R&D for mathematicians in applied jobs.

Mobility out of applied occupations back to R&D is monotonically decreasing and completely dies out within 12-14 years of employment, which might suggest that R&D related skills depreciate fast. Different disciplines experience different transition rates although very similar in pattern and timing. It peaks at 4 years of task-specific experience from as high as 0.14 for engineers to as low as 0.1 for mathematicians. The transition rates fall to 0.06 and 0.02 respectively by 14 years of experience. The observed difference in transition rates by discipline can suggest different depreciation rates of R&D skill or different return in R&D to experience in applied jobs. But overall the timing of the rates to R&D is consistent with a belief that returns or late entries to R&D are possible only within a short period of time.

Transitions out of S&E

Figures 4 and 5 show transition rates from R&D and application to non-S&E. The first observation is that in both cases the rates are much lower than those within S&E. Second, transitions rates are non-monotonic: the rates out of R&D are mostly single-peaked and similar in shape for all disciplines, while those out of applied occupations differ substantially by disciplines in shape and magnitude. Transitions out of applied jobs are lower than those out of R&D and do not exhibit a simple pattern. Third, transitions out of R&D die out after 16 years of R&D-specific tenure and are at their highest between 8 and 14 years in R&D, which corresponds to the period believed to be crucial for building a foundation for development of the scientific reputation. The peaks at 8, 10, or 12 years may correspond to several postdoctoral appointments, which are on average 2-3 years long or a combination of postdoctoral appointments and a tenure-track appointment, which is on average six years long. Some studies find that postdoctoral appointments became more common and much longer in the last decade or so, and in some fields they became a prerequisite for a tenure-track position

(Stephan and Ma (16), and Robin and Cahuzac (15)). It is possible that individuals who leave R&D for non-S&E occupations are those unable to land a tenure-track position. To test this hypothesis more explicitly, I control for the type of employment and number of the postdoctoral appointments when estimating a transition model described in more detail in the next subsection.

4 Model

In other to understand the reasons and the timing of the transitions, I develop an econometric duration model of transitions, and estimate it for four types of transitions: two between the S&E type jobs, and two out-of-S&E jobs.

4.1 Specification of the transition model

In every time period, an individual can be in one of three states denoted as $s(t)$, corresponding to the job-types: "R&D", "applied", or "non-S&E", denoted respectively as 1, 2, and 3. Let the rate of each transition be denoted by:

$$\theta_{ij}(t|X) = \lim_{\partial t \to 0} \frac{P[s(t+\partial t) = j | s(t) = i]}{\partial t}, \ i, j = 1, 2, 3, \ i \neq j$$

where X is a set of observed variables. Once state i is chosen, the duration of the stay in i is determined by $\theta_i = \sum_i \theta_{ij}, \ i{\neq}j$. Regardless of the initial state, an individual can exit into one of two other possible states. Suppose, there exist 3 latent duration variables, $\{T_j\}_{j=1}^{3}$, with T_j corresponding to the length of stay in the initial state i before exiting to the state j. In terms of duration analysis, they correspond to two competing risks that affect stay in the initial state. In empirical duration analysis literature it is often assumed that competing risks are independent, which is much easier to deal with computationally. In most economic problem this assumption is often very difficult to justify because individual characteristics (e.g. skills or preferences for each sector) are more likely to be correlated. This dependency can be captured through the joint distribution of some unobservable characteristic

ε over the three states, i.e. transition rates are independent only conditional on ε. For computational reasons, ε are often assumed to be discrete with a finite support and a joint probability mass function $G(\varepsilon)$. Identification of this kind of models requires data sets with multiple spells of the same type. However, the data set I am using in this study is not suitable for estimation of the model with dependent risks. Therefore, I follow the traditional approach and assume that the risks are independent conditional on the choice of the observable characteristics.

The set of observable characteristics X is assumed to include four groups of characteristics: demographic and educational characteristics DEM, job and activity characteristics JOB, research productivity variables $PROD$, and a set of macroeconomic variables $MACRO$. The first group DEM includes:

$$DEM = \{MARSTAT, CTZSTAT, ESL, MAJOR, CARN, TOP, NSE\}$$

where $MARSTAT$ is an indicator for "married", $CTZSTAT$ is a matrix of citizenship status indicators (native- and naturalized citizen, permanent or temporary resident), ESL controls for English-language proficiency (native- vs. foreign-), $MAJOR$ is an indicator of the field of PhD, $CARN$ is an indicator for graduates from the Carnegie Research I and II universities, TOP is an indicator for graduates from both Carnegie Research I/II and highly-ranked schools[5]. Finally, NSE is an indicator that a person had a BA or MA in non-S&E fields[6] "prior" to their PhD. This indicator is expected to control for non-S&E-specific skills or preference to non-S&E jobs. These variables were included to control for different outside options depending on personal characteristics and represent the baseline model.

The next set of characteristics JOB describes major activities and features of the job from which the transition originated:

$$JOB = \{SECTOR, RANK, POSTDOC, TEN, CARN2, ACT\}$$

[5] These include CalTech, UC Berkeley, Stanford, MIT, Harvard, Princeton and Yale.

[6] Social sciences, arts, humanities, business or law

where $SECTOR$ contains an indicator for the employment sector (academia, government, or industry), $RANK$ contains indicators for faculty ranks if individuals are employed in academia, TEN contain tenure status if employed in academia, $POSTDOC$ is an indicator for a postdoctoral appointment, $CARN2$ indicates that if the employer is academic it belongs to a Carnegie Research I/II category, and finally ACT indicates primary activities on the job and serve as proxies for occupation-specific skills.

The third set of characteristics include some research success parameters:

$$PROD = \{ART_{GRAD}, ART, PAPERS, PATENTS, NPDOC\}$$

where ART_{GRAD} and ART contain number of publications (at graduation and in total respectively), $PAPERS$ contains the number of working papers in two years preceding the survey, $PATENTS$ includes the total number of granted patents, and finally $NPDOC$ contains total number of postdoctoral appointments. This set of variables is expected to capture the effect of research productivity on transitions. $NPDOC$ controls for the length of underemployment to see if there is a "discouraged worker" effect on out-of-R&D transitions.

The final group, $MACRO$, contains the following variables:

$$MACRO = \{RD, UE, ENROLL, AWARDS\}$$

where RD is a percentage of R&D expenditures in the GDP, UE unemployment rate, $ENROLL$ is enrollment rates in undergraduate programs in sciences and engineering, $AWARDS$ is the number of awarded PhDs in S&E at graduation and in the year preceding the transition. All other variable in the group correspond to the year preceding the survey. These variables describe the labor market conditions: a) specific for R&D: RD and $AWARDS$, b) specific for application: UE and $ENROLL$, and c) specific for non-S&E: UE. R&D rates are a proxy for demand for research skill, and $AWARDS$ represents supply of the researchers, $ENROLL$ is a proxy for the demand for teachers, which represent a part of those employed in applied occupations, and finally UE represent overall economic conditions.

The descriptive statistics for the variables can be found in Table 3.

4.2 Functional forms

Each transition probability θ_{ij} is assumed to have the following functional form:

$$\theta_{ij}(t_i|X) = \theta_{0ij}(X) \cdot \theta_{ij}(t_i),$$

where $\theta_{ij}(t_i)$ is a baseline hazard, $\theta_{0ij}(X)$ is a systematic hazard. To derive the likelihood function we need to consider contribution of spells of different types. For a single spell k which does not end in an exit to either of the states (i.e. a right-censored spell), the likelihood contribution is simply the survival function, $S_k(t) = 1 - F_k(t) = \exp[-\sum_{i=1}^{t} \theta_k(i)]$. Contribution of the spells ending in either of the states would be equal to:

$$L_k = S_k \prod_j \theta_{kj}(t)^{1-\delta_{kj}(t)}$$

where $\delta_{kj}(t)$ is a Kroenecker delta equal to one if an exit from k to j occurs at time t and zero otherwise. Since each individual can have more than one spell, denote R a number of spells that an individual has in R&D, A in applied occupations, and N in non-S&E. Then for this individual, the likelihood contribution is:

$$L(\gamma; X)) = L_1 \prod_i^R L_{ri} \prod_j^A L_{aj} \prod_k^N L_{nk}, \tag{1}$$

where X is a matrix of observable characteristics, and γ is a vector of parameter values.

Initial conditions

I consider only spells that I observe from the start (no left-censored spells are used). Therefore, the only spells that require treatment for initial conditions are those corresponding to first jobs. The problem with such a spell is that the initial selection into each type of spells is non-random, and is correlated with observable and unobservable characteristics. There exist several methods to deal with the initial conditions. D'Addio and Rosholm (5) model the probability of taking a certain job as a function of observable characteristics, which comes at the cost of estimating more parameters. I adopt a method which assumes that:

$$L_1 = p_r^{d_r} p_a^{d_a} (1 - p_r - p_a)^{1-d_r-d_a},$$

where p_r, p_a, and p_n are empirical probabilities of observing an individual in R&D (r), application (a), or non-S&E (n) right after graduation. The choice of this approach is supported by the results of a multinomial probit model with correlated unobservable characteristics that was estimated separately on choices of the first jobs. The results show that none of the personal characteristics have significant effect on job choices. These results are not shown and are available upon request.

Finally, a likelihood contribution of an individual is:

$$L(\gamma; X) = L_1 \prod_i^R L_{ri} \prod_j^A L_{aj} \prod_k^N L_{nk} \tag{2}$$

4.3 Baseline hazard

I assume an exponential distribution of the survival times, which in turn implies exponential, i.e. constant, baseline hazard. This assumption can be applicable to labor market models if one slightly modifies it by allowing baseline hazards to be constant only on certain intervals, i.e. piecewise constant. I divide time in 15 periods of 2 years, with the 15th period being in $(28, \infty)$ interval. For the mapping principles between time and the intervals and modifications of the hazards functions to accommodate that see D'Addio and Rosholm (5). The baseline hazard becomes:

$$\theta_{ik}(t) = \exp(\theta_{ik}^{j(t)}), \quad j(t) \in (1, 15)$$

The final loglikelihood function is a sum of natural logarithms of (2), and is maximized with respect to the parameters on the observable characteristics β_{ij} and baseline hazard parameters θ_{ij}^m.

5 Estimation results

I estimate several specifications of the model. The first specification includes personal and employment characteristics, DEM and JOB. The next four specifications sequentially introduce four different research productivity variables from the $PROD$ set of characteristics: number of articles within the first 2 years after graduation, total number of publications, number of papers presented within 2 years preceding the transition, number of patents granted within 2 years prior to the transition. The sixth specification includes the number of postdoctoral appointments. The final specification includes labor market variables, $MACRO$: unemployment rate, share of the R&D expenditures in the GDP, enrollment rate in S&E programs, and finally the size of the cohort graduating in the year of the transition and at the time of the graduation of the individual. All seven specifications were estimated on the pooled sample.[7]

Mobility within S&E

Tables 5 and 7 present estimation results for the transitions between R&D and applied jobs. The first result is that scientists are more likely to move from R&D to applied jobs than engineers. This suggests that either competition in scientific R&D is more intense, or that scientists' R&D skills are more applicable in teaching or consulting than those of engineers. This is not true for mobility from applied jobs back to R&D: no difference by discipline in mobility rates is found. Those with degrees in non-S&E are more likely to switch to applied jobs and less likely to return to R&D. Individuals employed in Carnegie Research universities have lower probability of leaving for applied jobs, and higher probability to return to R&D. Those leaving R&D are more likely to be employed in academia and be involved in design and development than in basic or applied R&D. At the same time transitions to R&D from applied jobs are done mostly out of non-academic sectors. Having a tenure-track positions or being tenured increases probability of transferring to applied jobs

[7]Estimation by discipline produce similar results and are available from the author upon request.

compared to non-tenure track and postdoctoral appointments. This finding suggests that academic scientists invest in R&D early in their careers which enhances their total scientific knowledge, which they later "sell" to their students or clients as was suggested by Cater and Lew (4). The opposite however does not seem to be true: tenured academics are not more likely to switch from applied jobs to R&D than non-tenured ones, suggesting that predominantly teaching academics will not become involved in more intensive R&D after being tenured. The transitions are also less likely to happen from professional services as well. These results are more or less consistent for all seven specifications.

The next result is that neither of the productivity parameters affects the probability of transition from R&D to application. All of them have positive but insignificant effect except for the total number of articles, whose effect is negative. When including a control for productivity early in the career, the coefficient at the top school variable becomes positive and significant for transitions out of R&D. In addition, in all specifications that included productivity parameters, significance of having a postdoctoral appointment in out-of-R&D transitions disappears. On the contrary, higher R&D productivity has a significant positive effect on transitions back to R&D suggesting that returns or late entries to R&D are conditional on active publishing or patenting activity even if R&D is not a primary activity. The number of postdoctoral appointments does not have any effect for either type of transition.

The third result is that labor market conditions at the time of the transition matter for mobility within S&E. High R&D expenditures decrease mobility both out of and into R&D. At the same time high enrollment rates induce mobility of both types. The latter finding is consistent with a finding in Jones (10) that enrollment rates and faculty employment increase at similar rates, with faculty size changing with some lag. Next, the size of the cohort of new PhDs has a positive significant effect on out-of-R&D mobility. In an alternative specification (not shown) I included size of a cohort at the time of graduation to check for possible effect on out-of-R&D mobility caused by supply of PhDs and thus competition between them. My results showed positive but insignificant effect of the size of graduating cohort. I have also tried to include the size of the cohort in the individual's field supposing that individuals in different disciplines compete on different markets, but the results were similar: the cohort size had a small positive and insignificant effect.

A few things should be noted about the baseline hazard. Empirical transition rates from R&D to application have two peaks: after 4 years and after 8 years of the task-specific experience. The coefficients of the baseline hazard at 2-4 and 6-8 intervals remain highly significant in all specifications except when including the total number of articles. Including productivity early in career eliminates the effect of the 8th year of R&D-specific tenure, while the total number of postdoctoral appointments exclude the effect of the 4th year, even though both variables have no significant effect themselves. Transition out of applied jobs to R&D are single-peaked at 4 years on the job. The coefficient on the 2-4 interval of the baseline hazard remains positive and highly significant for all specifications except two: when one includes early productivity, and number of recent unpublished papers. In these two cases, the relative probability of exiting after four years actually falls but this effect is insignificant.

Mobility out of S&E

Tables 6 and 8 contain estimation results for the transitions out of S&E by origin. The first finding is that just as in the case of the within-S&E mobility, scientists are more likely to leave R&D for non-S&E than engineers. At the same time, there is no significant difference between scientists and engineers when it comes to mobility from applied jobs to non-S&E, with the computer scientists being the least likely to make the switch. One reason for that may be a higher competition in R&D positions for scientists. Alternatively, R&D skills of scientists are more valued outside S&E than those of engineers. More specifically these might be the design and development activities, noting the negative significance of the coefficients at basic or applied R&D.

Those with non-S&E degree are more likely to be switchers to non-S&E regardless of the origin of transition suggesting that these individuals possess some skills required in non-S&E jobs or have preferences towards non-S&E. All else equal, non-academics have higher odds to leave S&E. This might suggest that employment in the industry or government makes them more exposed to non-S&E employers, or that these sectors provide skills valued outside S&E.

The overall ability of the PhDs proxied by the quality of the degree granting school and publishing activity has the following effects. Graduates from the top schools and Carnegie Research I and II institutions have higher chances to leave R&D. When controlling for the research productivity directly, the positive effect of the Carnegie research institutions disappears, while the productivity parameters are all insignificant. Notably, the more postdoctoral positions the person had, the more likely (s)he is to leave R&D for non-S&E, which might suggest that inability to land a tenure-track job for any reason has a "discouraged worker" effect making an individual give up S&E altogether. Including the number of postdocs also eliminates any effect at the baseline hazards at the time intervals before 8-10 years of the R&D-specific tenure. This is consistent with the length of two to three postdoctoral appointment in length. The number of postdocs does not have the same effect on mobility out of applied occupations, where it has a negative sign and is insignificant.

Finally, labor market conditions also seem to have significant effects for mobility of this type. For example, high R&D expenditure relative to the GDP have a negative effect for out of S&E mobility. Enrollment rates do not have any impact on the out of R&D mobility, and have a negative but insignificant effect on the mobility out of application. Finally, the number of the newly minted PhDs induces mobility out of S&E, probably because it increases competition for the limited number of positions.

Conclusion

This paper studies career choices and mobility of white male doctorates in natural sciences and engineering. The first objective was to evaluate relevance of doctoral careers to S&E, and R&D in particular. Secondly, participation rates and transition patterns are compared among careers of different types. Finally, personal- and job characteristics, research productivity, and labor market conditions are evaluated in their effect on the frequency and timing of the transitions.

The first finding is that only 57% of all PhDs work in occupations oriented on R&D activities. Another 35% work in *application* rather than *creation* of the new knowledge in such tasks as teaching, software development, or professional services. I also find that, contrary to the common beliefs, 8% all S&E doctorates hold positions outside S&E fields to such sectors as finance or business services. The distribution of PhDs in all three types of jobs changes as their careers develop. Majority of doctorates begin their careers in R&D, 72%, and only 45% are still in R&D 30 years later. About 80% of them leave for R&D occupations, while the rest move out of S&E professions.

Most occupational transitions occur during the time believed to be critical for researchers to build scientific reputation. Analysis shows that it is mostly academic researchers on tenure-track or with tenure who switch to the applied jobs, which supports the predictions of the human capital theory. I also find that individuals who leave S&E are more likely to be employed in non-academic sectors and have non-S&E degrees prior to their PhD. The probability of leaving R&D increases with the number of postdoctoral appointments. Finally, these individuals do not exhibit high research productivity.

Analysis of the labor market conditions at the time of the transition show that mobility both within and out of S&E is very low when relative R&D expenditures are high, and grows when unemployment rates increase. Enrollment rates in science and engineering programs have similar effect on mobility but only within S&E.

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Appendix

Occupational Categories in Science and Engineering

Major category	Minor categories of occupation
	Science and Engineering
Computer & Mathematical Scientists	Computer & Information Scientists Mathematical Scientists Postsecondary Teachers - Computer & Mathematical Sciences
Life Scientists	Agricultural & Food Scientists Biological Scientists Environmental Life Scientists Postsecondary Teachers - Life & Health Sciences
Physical Scientists	Chemists, except Biochemists Earth Scientists, Geologists & Oceanographers Physicists & Astronomers Other Physical Scientists Postsecondary Teachers - Physical Sciences
Engineers	Aerospace & Related Engineers Chemical Engineers Civil & Architectural Engineers Electrical & Related Engineers Industrial Engineers Mechanical Engineers Other Engineers Postsecondary Teachers - Engineering
	Non-Sciences and Engineering
Non-S&E occupations	Managers & Administrators Health related occupations Teachers, except S&E Postsecondary Teachers Non-S&E Postsecondary Teachers Social Services & Related occupations Technologists & Technicians Sales & Marketing occupations Art, Humanities & related occupations Other non-S&E occupations

SOURCE: SESTAT: A Tool for Studying Scientists and Engineers in the United States. Division of Science Resources Studies. NSF.

Occupation	Field of the PhD			
	Comp and Math	Life sci	Phy sci	Engineering
Comp and Math Scientists	0.2603	0.0033	0.0259	0.0501
Comp and Math Teach.	0.4941	0.0093	0.0075	0.0144
Life Scientists	0.0029	0.3704	0.0422	0.0070
Life Teachers	0.0000	0.2167	0.0126	0.0033
Physicists and astronomers	0.0068	0.0184	0.3971	0.0271
Physics Teachers	0.0010	0.0124	0.2034	0.0041
Engineers	0.0254	0.0082	0.0572	0.4465
Engineering Teachers	0.0078	0.0020	0.0112	0.1851
Social scientists	0.0000	0.0038	0.0009	0.0004
Social sci Teachers	0.0049	0.0024	0.0006	0.0012
Managers	0.1360	0.1823	0.1876	0.2089
Non-S&E Teachers	0.0157	0.0606	0.0092	0.0123
Other Non-S&E	0.0450	0.1099	0.0445	0.0398

Table 1: Occupational choice in S&E by discipline

Occupation	Primary activity		
	R&D	Teaching, consulting, prof.svcs.	Management and finance
Scientists	0.8412	0.0536	0.0778
Engineers	0.7079	0.1207	0.1350
S&E teachers	0.2938	0.6663	0.0319
Managers	0.2057	0.0908	0.6642
Non-S&E others	0.1791	0.1537	0.5427

Table 2: Primary activities of PhDs by occupation

	R&D jobs	applied jobs	non-S&E	Overall
Age	43.70	46.85	48.51	45.22
Citizen, native	0.811	0.841	0.820	0.813
Citizen, naturalized	0.090	0.091	0.130	0.091
Permanent resident	0.072	0.051	0.042	0.063
Temporary resident	0.020	0.013	0.011	0.016
Married	0.471	0.452	0.670	0.470
Non-English speaker	0.109	0.128	0.114	0.117
Comp.sciences	0.018	0.029	0.011	0.022
Mathematics	0.040	0.109	0.060	0.067
Health/Life sciences	0.445	0.439	0.433	0.442
Physics	0.308	0.249	0.296	0.286
Engineering	0.179	0.163	0.200	0.175
Public university graduate	0.651	0.681	0.680	0.662
Graduate of Research I and II	0.867	0.849	0.854	0.860
Top-school graduate	0.158	0.134	0.155	0.149
Fraction with non-S&E degrees	0.049	0.089	0.128	0.069
# papers early in career	2.012	2.290	1.170	2.014
Academic sector	0.404	0.658	0.178	0.478
Government sector	0.124	0.064	0.110	0.102
Employed at Carnegie I$\times$Academe	0.243	0.222	0.106	0.225
Postdoctorate	0.116	0.020	0.0056	0.074
Tenure-track$\times$Academe	0.063	0.123	0.019	0.081
Tenured$\times$Academe	0.146	0.353	0.095	0.217
Full-time professor$\times$Academe	0.092	0.207	0.072	0.132
Unemployment rate				0.0636[a]
R&D in GDP				0.0248[b]
Enrollment, thousands				12,957[c]
PhD awards in S&E				15,809[d]
Number spells	9978	7574	2363	
Number of individuals				14988

[a]Source: US Bureau of Labor Statistics.
[b]Source: National Science Foundation/Division of Science Resources Statistics.
[c]Source: U.S. Department of Education, National Center for Education Statistics, IPEDS
[d]Source: National Science Foundation/Division of Science Resources Statistics.

Table 3: Summary statistics

	Destination		
Origin	R&D	Application	Non-S&E
R&D	14,734	7,521	1,781
	0.6130	0.3129	0.0741
Application	6,635	11,326	1,564
	0.3398	0.5801	0.0801
Non-S&E	1,382	1,513	3,254
	0.2248	0.2461	0.5292

Table 4: Average transition rates.

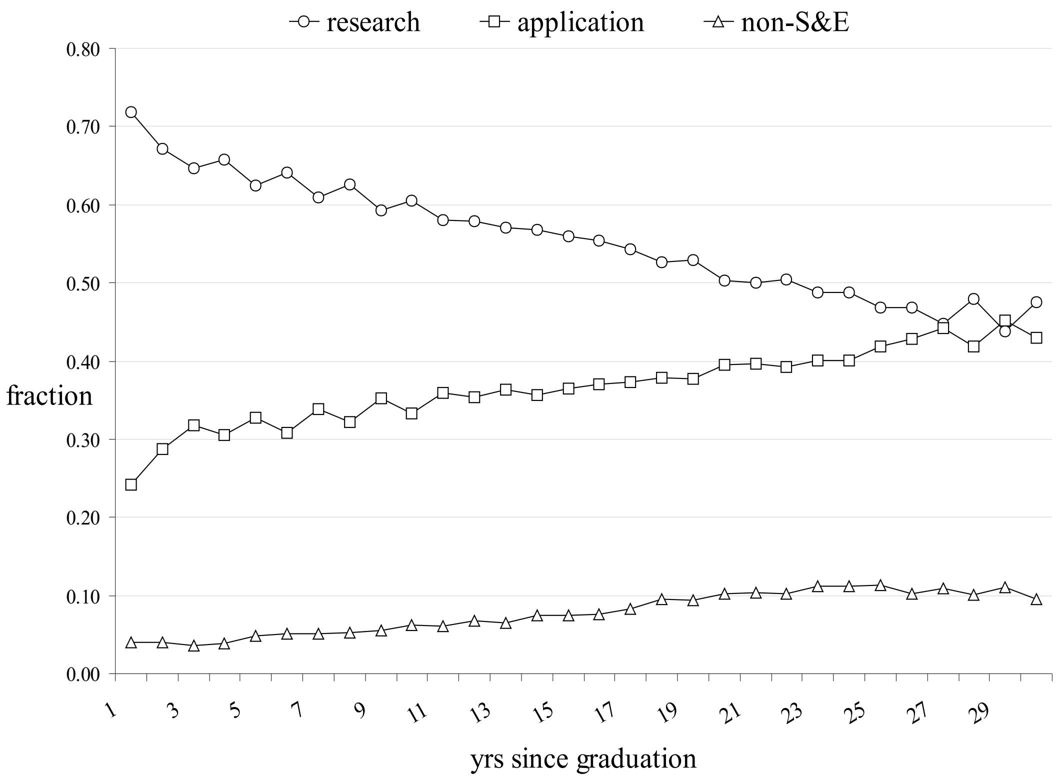

Figure 1: Participation rates in three type of jobs, by years since graduation

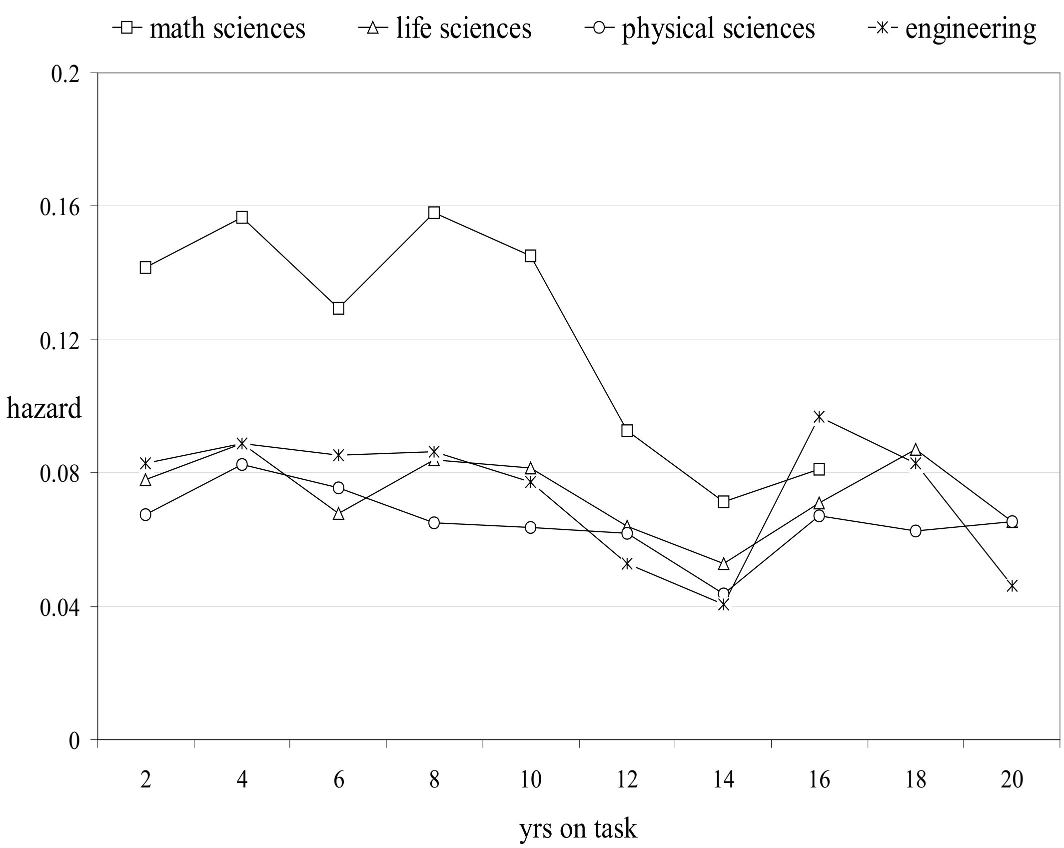

Figure 2: Transitions from R&D to application, by discipline

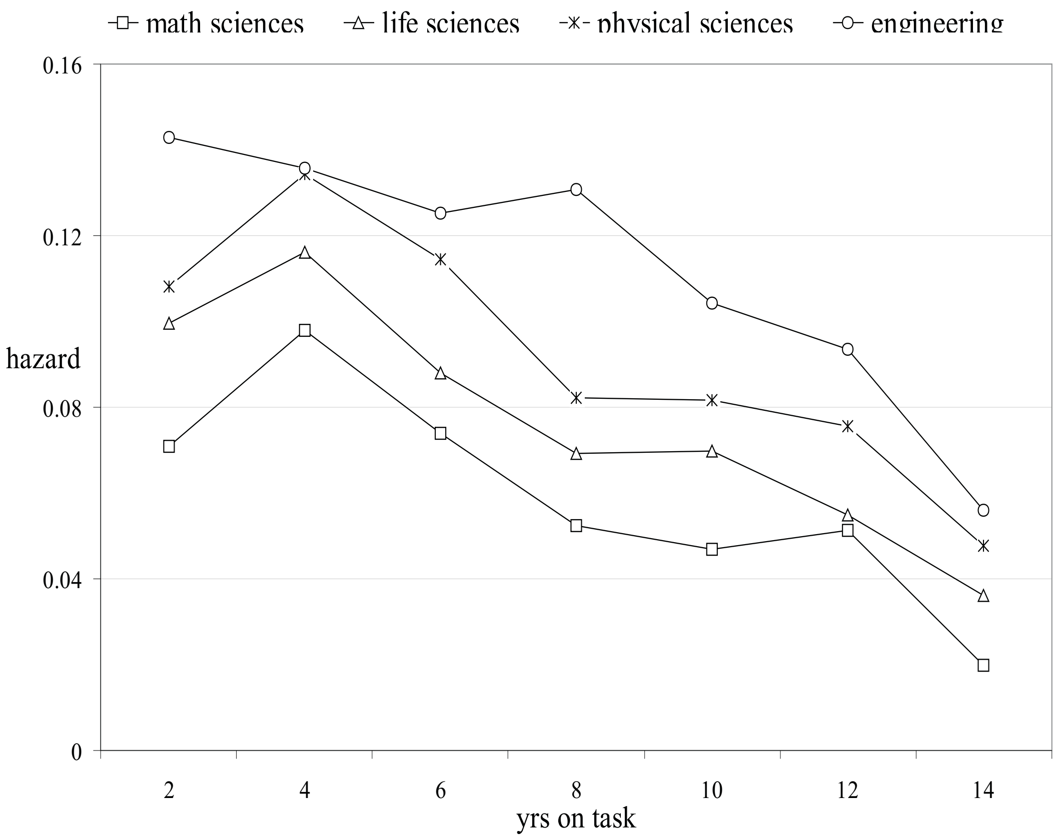

Figure 3: Transitions from application to R&D, by discipline

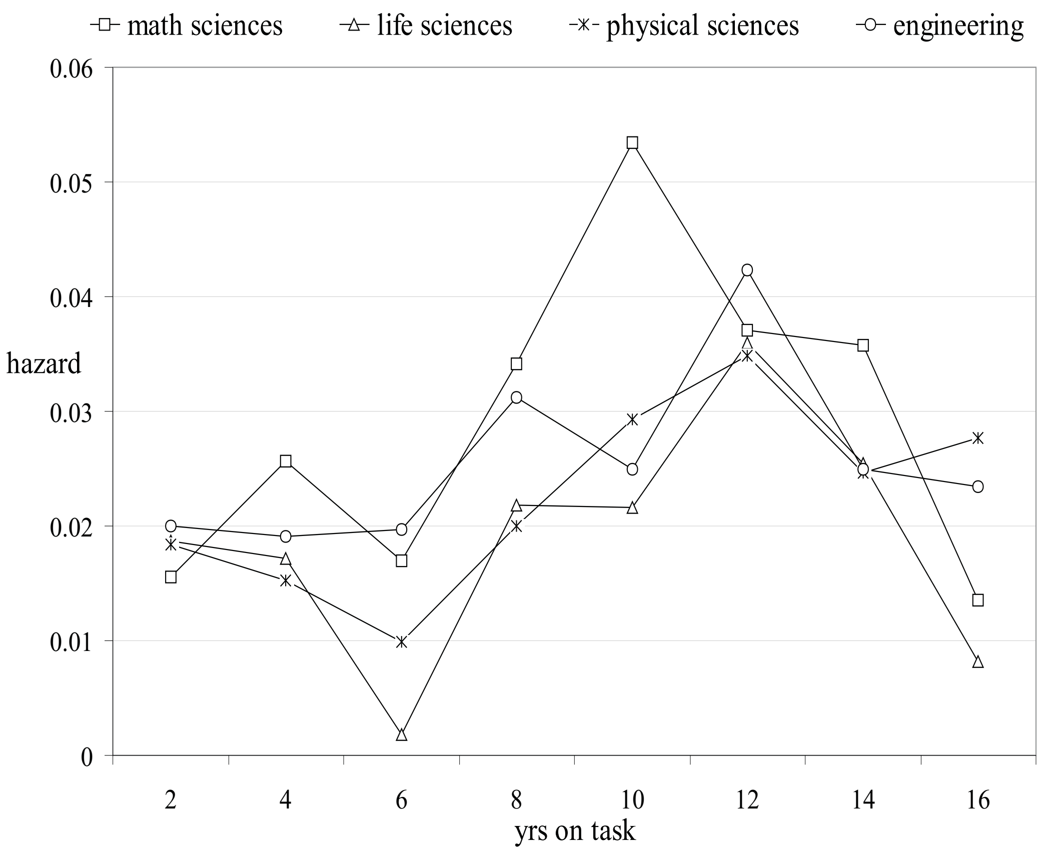

Figure 4: Transitions from R&D to non-S&E, by discipline

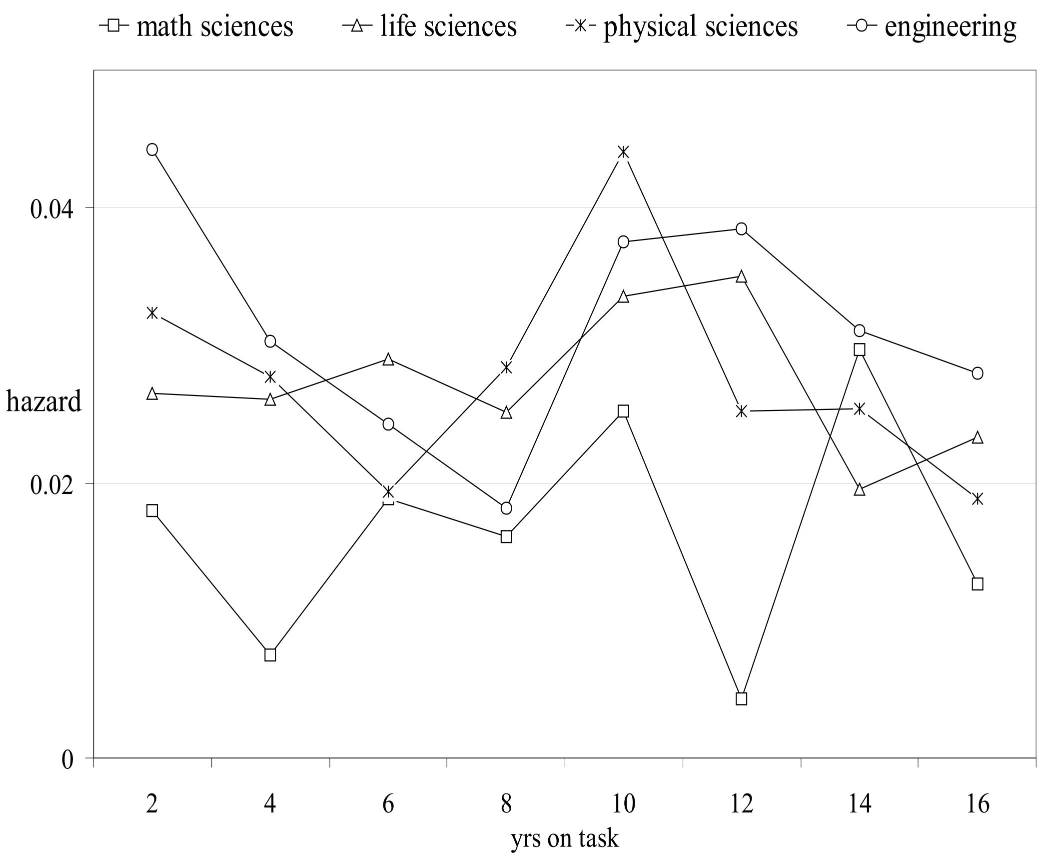

Figure 5: Transitions from application to non-S&E, by discipline

Variable	Coeff	St.Err		Coeff	St.Err		Coeff	St.Err		Coeff	St.Err	
computer sci	0.2668	(0.1027)	***	0.2962	(0.2502)		0.4345	(0.7207)		0.3839	(0.1030)	***
math sci	0.3627	(0.0677)	***	0.3217	(0.1500)	**	0.3958	(0.1617)	**	0.3798	(0.0678)	***
life sci	0.1544	(0.0437)	***	0.2068	(0.0948)	**	-0.0483	(0.1046)		0.2056	(0.0438)	***
physical sci	0.1568	(0.0450)	***	0.1062	(0.1032)		-0.0295	(0.1063)		0.1995	(0.0451)	***
native citizen	-0.7241	(0.0369)	***	-0.5622	(0.0807)	***	-0.7916	(0.0639)	***	-0.6425	(0.0414)	***
naturalized citizen	-0.2674	(0.0698)	***	-0.3284	(0.2163)		-0.2866	(0.1602)	*	-0.3327	(0.0716)	***
non-English speaker	-0.0038	(0.0518)		-0.0668	(0.1138)		-0.0528	(0.1040)		0.0340	(0.0545)	
Top school	-0.0327	(0.0412)		0.0254	(0.0942)		-0.0618	(0.0738)		-0.0291	(0.0413)	
non-S&E degree	0.1037	(0.0626)	*	-0.0119	(0.1322)		0.1355	(0.1062)		0.0650	(0.0628)	
Carnegie research	-0.3403	(0.0431)	***	-0.4694	(0.0949)	***	-0.4674	(0.0730)	***	-0.3378	(0.0436)	***
sector - industry	-0.8674	(0.0496)	***	-0.9205	(0.1225)	***	-0.9479	(0.0891)	***	-0.8528	(0.0501)	***
sector - government	-0.7476	(0.0667)	***	-0.6504	(0.1557)	***	-0.8091	(0.1291)	***	-0.7121	(0.0670)	***
activity - applied research	-3.0123	(0.1005)	***	-2.9527	(0.1756)	***	-2.8237	(0.1711)	***	-3.0990	(0.1006)	***
activity - basic research	-3.4899	(0.1087)	***	-3.7248	(0.2175)	***	-3.2968	(0.1408)	***	-3.5742	(0.1089)	***
activity - management	-0.2267	(0.0339)	***	-0.7339	(0.0912)	***	-0.1907	(0.0641)	***	-0.3224	(0.0352)	***
postdoc x acad	-0.4843	(0.1416)	***	-0.5262	(0.3901)		-0.5261	(0.1807)	***	-0.3729	(0.1419)	***
tenure track x acad	0.1490	(0.0630)	**	0.2736	(0.1309)	**	0.2265	(0.0949)	**	0.2091	(0.0634)	***
tenured x acad	0.2490	(0.0506)	***	0.3073	(0.1158)	***	0.2911	(0.0894)	***	0.2245	(0.0505)	***
# total articles				-0.0017	(0.0037)							
# of postdocs							0.0542	(0.0460)				
UE rate										0.1935	(0.0175)	***
R&D in GDP										-1.4008	(0.1080)	***
current enrollment level										0.0531	(0.0075)	***
cohort size										0.0001	(0.0000)	***
Baseline hazard												
2-4	0.1133	(0.0403)	***	0.0639	(0.1310)		0.0368	(0.0742)		0.3097	(0.0426)	***
4-6	-0.0274	(0.0473)		0.0460	(0.1421)		-0.0884	(0.0873)		0.2644	(0.0507)	***
6-8	0.1585	(0.0494)	***	0.1314	(0.0913)		0.2030	(0.0867)	**	0.3657	(0.0525)	***
8-10	0.1194	(0.0635)	*	0.0664	(0.1455)		0.1331	(0.1185)		0.2370	(0.0658)	***
10-12	-0.2958	(0.0746)	***	-0.3756	(0.2439)		-0.3392	(0.1353)	**	-0.0744	(0.0760)	
constant	-0.9223	(0.0731)	***	-0.0036	(0.0064)		-0.8055	(0.1590)	***	-0.8051	(0.3437)	**
N observations	27535			5222			10094			27535		
N individuals	8369			3822			2565			8369		
N failures	4363			860			1331			4363		
LR	6157.9			1638.4			2344.9			6504		

*** - significant at 10%
** - signficiant at 5%
* - significant at 1%

Table 5: Proportional hazard model estimation results, R&D to application

Variable	Coeff	St.Err		Coeff	St.Err		Coeff	St.Err		Coeff	St.Err	
computer sci	-0.2263	(0.2586)		-0.1147	(0.7311)		1.7613	(1.0482)	*	-0.0101	(0.2590)	
math sci	0.3187	(0.1523)	**	0.6334	(0.3791)	*	0.4915	(0.5620)		0.3980	(0.1527)	***
life sci	0.5119	(0.0811)	***	0.5708	(0.2128)	***	0.7236	(0.2591)	***	0.5747	(0.0820)	***
physical sci	0.2426	(0.0829)	***	0.0513	(0.2390)		0.4613	(0.2631)	*	0.3110	(0.0833)	***
native citizen	-1.0550	(0.0716)	***	-1.4927	(0.1790)	***	-1.2508	(0.1315)	***	-0.9820	(0.0780)	***
naturalized citizen	-0.4363	(0.1525)	***	-0.9641	(0.6080)		-0.3674	(0.3772)		-0.3703	(0.1537)	**
non-English speaker	-0.2930	(0.1157)	**	-0.6205	(0.2850)	**	-0.2625	(0.2332)		-0.1544	(0.1179)	
Top school	0.1566	(0.0768)	**	0.0551	(0.2271)		-0.0779	(0.1527)		0.1897	(0.0769)	**
non-S&E degree	0.7044	(0.0934)	***	0.4896	(0.2377)	**	0.7150	(0.1772)	***	0.4896	(0.0938)	***
Carnegie research	0.4685	(0.1509)	***	0.8388	(0.3199)	***	0.7124	(0.2439)	***	0.2547	(0.1587)	
sector - industry	1.0356	(0.1653)	***	0.8331	(0.3721)	**	1.2594	(0.2873)	***	0.7837	(0.1673)	***
sector - government	0.7460	(0.1822)	***	0.7845	(0.4235)	*	1.1765	(0.3200)	***	0.5550	(0.1837)	***
activity - applied research	-1.8366	(0.1035)	***	-2.4976	(0.2835)	***	-2.2632	(0.2146)	***	-2.0390	(0.1040)	***
activity - basic research	-2.5538	(0.1755)	***	-2.7374	(0.3732)	***	-2.5340	(0.2482)	***	-2.7489	(0.1776)	***
activity - management	0.0776	(0.0629)		-0.2376	(0.1770)		-0.1756	(0.1271)		-0.0337	(0.0633)	
postdoc x acad	-0.5468	(0.3278)	*	-1.3132	(1.0370)		-0.4421	(0.3829)		-0.4047	(0.3282)	
tenure track x acad	-0.7472	(0.3088)	**	-0.6685	(0.5761)		-1.1032	(0.5521)	**	-0.6183	(0.3096)	**
tenured x acad	-0.0387	(0.1755)		-0.2648	(0.3574)		-0.1671	(0.3137)		-0.0324	(0.1770)	
# articles				0.0017	(0.0094)							
# of postdocs							0.1893	(0.0820)	**			
UE rate										0.4682	(0.0384)	***
R&D in GDP										-1.4816	(0.2697)	***
current enrollment level										0.0098	(0.0188)	
cohort size										0.0003	(0.0000)	***
Baseline hazard												
2-4	-0.2015	(0.0862)	**	-0.6998	(0.3529)	**	-0.1694	(0.1685)		0.1902	(0.0887)	**
4-6	-0.3263	(0.0987)	***	-0.2017	(0.2858)		-0.1612	(0.1908)		0.3123	(0.1043)	***
6-8	0.1093	(0.0927)		0.2089	(0.1990)		0.1776	(0.1872)		0.3815	(0.1001)	***
8-10	0.2087	(0.1107)	*	0.2657	(0.3810)		0.5116	(0.2060)	**	0.1857	(0.1134)	
10-12	0.2934	(0.1040)	***	-0.3753	(0.4653)		0.4782	(0.1881)	**	0.2602	(0.1050)	**
constant	-3.3168	(0.2025)	***	0.0145	(0.0155)		-3.9084	(0.4267)	***	-7.5053	(0.8443)	***
N observations	24296			4517			9062			24296		
N individuals	6754			3277			2114			1220		
N failures	1220			169			326			8592		
LR	1581.5			391.91			608.19			2037		
*** - significant at 10%												
** - signficiant at 5%												
* - significant at 1%												

Table 6: Proportional hazard model estimation results, R&D to non-S&E

Variable	Coeff	St.Err		Coeff	St.Err		Coeff	St.Err		Coeff	St.Err	
computer sci	0.0618	(0.1010)		0.2417	(0.2400)		-0.5479	(0.4675)		0.1184	(0.1012)	
math sci	-0.0341	(0.0699)		-0.0068	(0.1624)		-0.0107	(0.1894)		-0.0211	(0.0702)	
life sci	-0.0282	(0.0488)		-0.0291	(0.1045)		0.0770	(0.1253)		-0.0221	(0.0491)	
physical sci	0.0026	(0.0506)		-0.1189	(0.1136)		-0.0660	(0.1271)		0.0287	(0.0507)	
native citizen	-0.5902	(0.0401)	***	-0.7294	(0.0943)	***	-0.5888	(0.0769)	***	-0.6328	(0.0460)	***
naturalized citizen	-0.2525	(0.0811)	***	-0.5811	(0.2531)	**	-0.5304	(0.2024)	***	-0.3972	(0.0830)	***
non-English speaker	-0.0851	(0.0583)		-0.0639	(0.1375)		-0.1100	(0.1318)		-0.1130	(0.0611)	*
Top school	0.0492	(0.0460)		0.0117	(0.1039)		0.0706	(0.0878)		0.0162	(0.0462)	
non-S&E degree	-0.2250	(0.0729)	***	-0.1221	(0.1442)		-0.0628	(0.1387)		-0.2390	(0.0733)	***
Carnegie research	0.6651	(0.0506)	***	0.6319	(0.1057)	***	0.7587	(0.0951)	***	0.6308	(0.0508)	***
sector - industry	0.2547	(0.0647)	***	0.2037	(0.1466)		0.2405	(0.1246)	*	0.2820	(0.0652)	***
sector - government	0.3754	(0.0771)	***	0.3606	(0.1748)	**	0.5770	(0.1488)	***	0.3882	(0.0773)	***
activity - teaching	-4.2420	(0.1852)	***	-3.5085	(0.2742)	***	-4.2424	(0.3576)	***	-4.2776	(0.1853)	***
activity - prof.services	-6.0374	(1.0003)	***	-16.4853	(366.3630)		-18.4364	(784.6619)		-6.0520	(1.0004)	***
activity - management	0.0466	(0.0435)		-0.3574	(0.1210)	***	-0.0810	(0.0911)		0.0136	(0.0440)	
tenure track x acad	-0.0074	(0.0897)		-0.0969	(0.1700)		-0.0146	(0.1469)		0.1276	(0.0903)	
tenured x acad	0.0307	(0.0600)		-0.1064	(0.1297)		-0.0227	(0.1095)		0.0652	(0.0600)	
# patents granted												
# of postdocs							0.0015	(0.0005)	***			
UE rate										0.1865	(0.0194)	***
R&D in GDP										-1.5968	(0.1203)	***
current enrollment level										0.0591	(0.0084)	***
cohort size										0.0001	(0.0000)	***
Baseline hazard												
2-4	0.2326	(0.0431)	***	-0.0464	(0.1339)		0.2186	(0.0869)	**	0.3953	(0.0453)	***
4-6	0.1189	(0.0520)	**	0.0492	(0.1426)		0.1647	(0.1044)		0.3494	(0.0549)	***
6-8	0.0995	(0.0624)		-0.0582	(0.1287)		0.1963	(0.1281)		0.2876	(0.0649)	***
8-10	0.0330	(0.0814)		0.2573	(0.2023)		0.2090	(0.1555)		0.2249	(0.0834)	***
10-12	-0.2129	(0.0948)	**	-0.0320	(0.3012)		0.0724	(0.1822)		0.0612	(0.0965)	
constant	-1.6775	(0.0885)	***	-0.0055	(0.0077)		-1.6880	(0.2021)	***	-0.6354	(0.3700)	*
N observations	16932			2766			4267			16932		
N individuals	6035			2195			1478			6035		
N failures	3400			664			855			3400		
LR	4324.6			1054			1252.1			4623		

*** - significant at 10%
** - signficiant at 5%
* - significant at 1%

Table 7: Proportional hazard model estimation results, application to R&D.

Variable	Coeff	St.Err		Coeff	St.Err		Coeff	St.Err		Coeff	St.Err	
computer sci	-1.2169	(0.3616)	***	-0.9988	(1.0254)		-12.5805	(400.2047)		-1.1660	(0.3617)	***
math sci	-0.2137	(0.1429)		-0.6640	(0.4996)		-0.2089	(0.4626)		-0.2241	(0.1433)	
life sci	0.1032	(0.0931)		0.0333	(0.2773)		0.0815	(0.2912)		0.0954	(0.0938)	
physical sci	-0.0167	(0.0966)		-0.1975	(0.2994)		-0.1027	(0.2855)		0.0206	(0.0970)	
Top school	0.0457	(0.0931)		-0.0687	(0.2990)		-0.1784	(0.2240)		0.0326	(0.0932)	
non-S&E degree	0.4161	(0.0952)	***	0.6287	(0.2820)	**	0.5231	(0.2223)	**	0.2978	(0.0966)	***
native citizen	-0.5773	(0.0808)	***	-1.1647	(0.2461)	***	-0.6242	(0.1778)	***	-0.7078	(0.0894)	***
naturalized citizen	-0.2423	(0.1684)		-1.2356	(0.7663)		-0.6298	(0.4751)		-0.3559	(0.1699)	**
non-English speaker	-0.2551	(0.1253)	**	0.1198	(0.3460)		-0.4424	(0.3304)		-0.2504	(0.1291)	*
Carnegie research	0.7247	(0.1186)	***	1.4508	(0.2977)	***	1.1411	(0.2480)	***	0.6993	(0.1190)	***
sector - industry	1.2787	(0.1380)	***	2.1960	(0.4717)	***	1.8794	(0.3509)	***	1.1808	(0.1390)	***
sector - government	0.8532	(0.1644)	***	1.2589	(0.5941)	**	1.4834	(0.4257)	***	0.8103	(0.1650)	***
activity - teaching	-1.4113	(0.1289)	***	-1.4298	(0.3590)	***	-1.5691	(0.3075)	***	-1.4371	(0.1295)	***
activity - prof.services	-1.3669	(0.1540)	***	-1.3720	(0.4007)	***	-1.6875	(0.3366)	***	-1.4760	(0.1549)	***
activity - management	0.4355	(0.0722)	***	0.2039	(0.2351)		0.3629	(0.1665)	**	0.2761	(0.0728)	***
tenure track x acad	-0.4811	(0.2359)	**	0.3312	(0.6000)		-0.2044	(0.5132)		-0.4243	(0.2376)	*
tenured x acad	-0.2773	(0.1416)	*	0.1353	(0.4825)		0.0250	(0.3598)		-0.2625	(0.1426)	*
# articles				-0.0081	(0.0132)							
# of postdocs							-0.1017	(0.1497)				
UE rate										0.2883	(0.0396)	***
R&D in GDP										-1.1466	(0.2630)	***
current enrollment level										-0.0281	(0.0209)	
cohort size										0.0001	(0.0000)	***
Baseline hazard												
2-4	-0.0259	(0.0881)		-0.6022	(0.3631)	*	-0.0885	(0.2070)		0.1629	(0.0900)	*
4-6	-0.0553	(0.1037)		-0.9984	(0.5225)	*	0.0458	(0.2268)		0.2069	(0.1066)	*
6-8	0.1003	(0.1152)		-0.0399	(0.3375)		0.5252	(0.2398)	**	0.1947	(0.1189)	
8-10	0.3331	(0.1217)	***	0.5009	(0.4520)		-0.0595	(0.3760)		0.3251	(0.1239)	***
10-12	0.1578	(0.1429)		-0.0998	(0.6121)		0.4071	(0.3056)		0.1814	(0.1437)	
constant	-3.3052	(0.1836)	***	0.0202	(0.0203)		-3.7332	(0.5073)	***	-4.4599	(0.8064)	***
N observations	14445			7052			3582			14445		
N individuals	4761			3215			1133			4761		
N failures	982			663			184			982		
LR	1115.6			1009.7			289.56			1270		

*** - significant at 10%
** - signficiant at 5%
* - significant at 1%

Table 8: Proportional hazard model estimation results, application to non-S&E.