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THE PERFECT MATCH? CORRELATES OF JOB PLACEMENT AMONG PHD
EARNERS

By

Andrea K. Johnson

A THESIS

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THE PERFECT MATCH? CORRELATES OF JOB PLACEMENT AMONG PHD
EARNERS

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University of Nebraska, 2019

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Earning a doctorate in a field implies a strong desire to stay in that field, yet not all who earn a PhD do stay in their field. Therefore this study assumes that those who leave their chosen field do so either involuntarily or because of strong “pull” factors. Using the Survey of Doctorate Recipients (2015), this study examines a variety of factors that affect job placement among PhD recipients, specifically efforts to “match” doctoral field credentials with occupational outcomes. Analyses explicitly test classic assumptions underlying Human Capital Theory, while also taking into account demographic characteristics social capital differences. Findings indicate that demographic characteristics (such as gender, age and citizenship), human capital (including doctoral and bachelor field type) and social capital influence job placement. Institutional context also plays a role. Perhaps the most surprising finding is that approximately 40-45% of respondents find a job outside of their doctorate field of study, specifically those with doctorates in Biology, Agricultural and Environmental Sciences, Physical and Related Sciences, Social and Related Sciences and Engineering. Identifying these individual- and institutional-level factors helps understand both who is finding a job credential match and whether or not that match is a lucrative one.

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INTRODUCTION

Once scientists earn a terminal degree in their field (usually a PhD), one objective may be to find a career within their field of study commensurate with their extensive and intensive academic training obtained within that field. This assumption is not only held by individuals, but by educational and occupational institutions. The United States, for instance, produces approximately 20,000 science doctorates annually, second only to China (Cyranoski et al. 2011). Although the supply of doctorates has increased over the past few decades, the demand for PhDs in traditional academic jobs has decreased. In 1973, for instance, 55% of doctorates in the biological sciences secured tenure-track positions and 2% worked in untenured track positions within 6 years after completion of their degrees. A little over 30 years later, only 15% of doctorates in the biological sciences secured tenure-track positions and 18% received untenured academic positions within 6 years of graduation (Cyranoski et al. 2011). Consequently, an increasing number of PhD recipients have had to look outside of their field of study for a well-paying job. These increasing job/education mismatches have created significant repercussions, including but not limited to, consequences for wages, job satisfaction and mobility (Bender and Heywood 2011).

The supply and demand of PhDs has been steadily at odds over the past few decades within the academic realm, but this trend does not fully portray field matches in business or government jobs. Nor does it explain *who* among this educational elite is more likely to end up in a field outside their doctoral field of study. Extant research indicates that job placement is strongly influenced not only by merit and pedigree but also by membership in specific demographic groups (Ma 2011). For instance, significant

gender differences exist in occupational outcomes even for individuals with similar degrees and training (Mann and DiPrete 2013). Consequently, gender segregation is widespread across fields, disciplines and levels of education (Acker 1990a), even though it causes at the highest levels of expertise have not yet been examined (Frehill, Abreu, and Zippel 2015).

Much existing research places doctoral job-education mismatches as predictors of other events, as job/field mismatches have consequences for wages, job satisfaction and mobility (Bender and Heywood 2011). In contrast, few studies have examined institutional or individual-level factors associated with a PhD scientist holding a job outside of the field of their PhD.

Using data from the *2015 Survey of Doctorate Recipients* (National Science Foundation, 2019), this thesis will examine how demographic characteristics, human capital and social capital explain PhD credential/job matches. These factors could contribute to the stratification of specific populations into PhD credential mismatches. This stratification is associated with an individual's lack of occupational opportunities (including job satisfaction, autonomy and higher wages), while whole fields lose intellectual human capital, creativity and growth.

LITERATURE REVIEW

Studies of individuals whose educational credentials do not match their occupation primarily focus on the *outcomes* of credential mismatches. Credential mismatches can negatively affect individual wages and limit on-the-job searches (Allen and van der Velden 2001), can increase job turnover (Hersch 1991), and even influence job satisfaction (Tsang and Levin 1985). We know far less about *what type of individuals*

face credential-job match and mismatches. On one hand, perhaps women or minorities, who are tracked into specific fields (Riegle-Crumb et al. 2012) are more likely to face credential-job mismatches, due to their limited career options (England and Li 2006:200). On the other hand, perhaps it is advantageous for other, privileged individuals, such as white males, to find a job outside of their doctoral field of study and the mere possession of a PhD could elevate these individuals into more lucrative fields.

The PhD track is particularly interesting, as the educational goal of PhD students is to narrow their field of study and accumulate knowledge within that specific category (Jones 2018). Collegiate tracks at lower levels of educational attainment can include both specific and general scholarship, and a liberal arts education can lead to a variety of jobs and careers (Robst 2007). By focusing on the PhD level of educational credentials, we can assess what differential credential-job match patterns emerge at the highest level of education.

This raises the question: Under which conditions are PhD holders, specifically STEM PhD earners, are likely to hold jobs outside their PhD field of study? It is important to understand the factors promoting or impeding a credential-job match for PhD holders. By assessing predictors of having a job that matches a scientist's field of study, including demographics and human and social capital factors, we can understand the potentially stratified pathways that can develop at elite educational levels.

Conceptual Framework

Using Sociology to Respond to an Economic Theory

Human Capital Theory is a rational choice theory used explain the distribution of workers within the labor market (Nafukho, Hairston, and Brooks 2004). The theory has

undergone many iterations (Fitz-enz 2000; Schultz 1961), but the underlying outcome remains the same: a person's education and training denotes their productivity, and therefore value, as a working member of the labor market. To summarize, Human Capital Theory posits that the skills and qualities of individuals determine their job placement and wages. Researchers still use Human Capital Theory (HCT) and related classic supply and demand arguments to explain PhD credential match or mismatches. A recent analysis of almost 6,000 humanities PhDs, for example, uses this line of argument to explain mismatches for degree holders in fields that outstrip the number of jobs available. (Jaschik 2017).

The HCT model assumes both laborers and employers are rational actors, constantly engaging in a cost-benefit analysis (Doppelt 2019). This model also assumes that the educational credentials an individual earns will be enough to find a job that matches those credentials and that there should be no systematic differences between groups in who ends up getting matched – only personal preferences of job seekers and labor market constraints, rather than prejudice or exclusion. Human Capital has received criticism across disciplines (Bozeman, S. Dietz, and Gaughan 2001; Corley et al. 2019) for its narrow definition.

Sociologists have critiqued HCT for a long time because the model fails to acknowledge other forms of capital, such as social capital, or cultural context. In response to this critique, some social scientists have indeed expanded the definition of Human Capital Theory to include more forms of capital. The Scientific and Technical Human Capital Model (STHC), for instance, includes social capital with the traditional HCT model (Bozeman et al. 2001). Although this model is conceptually more sound, others

point out that it also fails to account for social context, context that is grounded in cultural and organizational practices and institutional dynamics to explain job market outcomes (Corley et al. 2019). These alternative drivers (social context) have been coalesced into the concept of “inequality regimes” (coined by Joan Acker) (Acker 2006). This implications of demographic characteristics (such as gender and race) are socially constructed (Risman 2004) and are subject to hidden inequality regimes that systematically stratify individuals into different occupational choices. Similar to Bozeman and Corley, I expand on HCT to incorporate not only human capital, but also social capital and social context (measured by demographic characteristics).

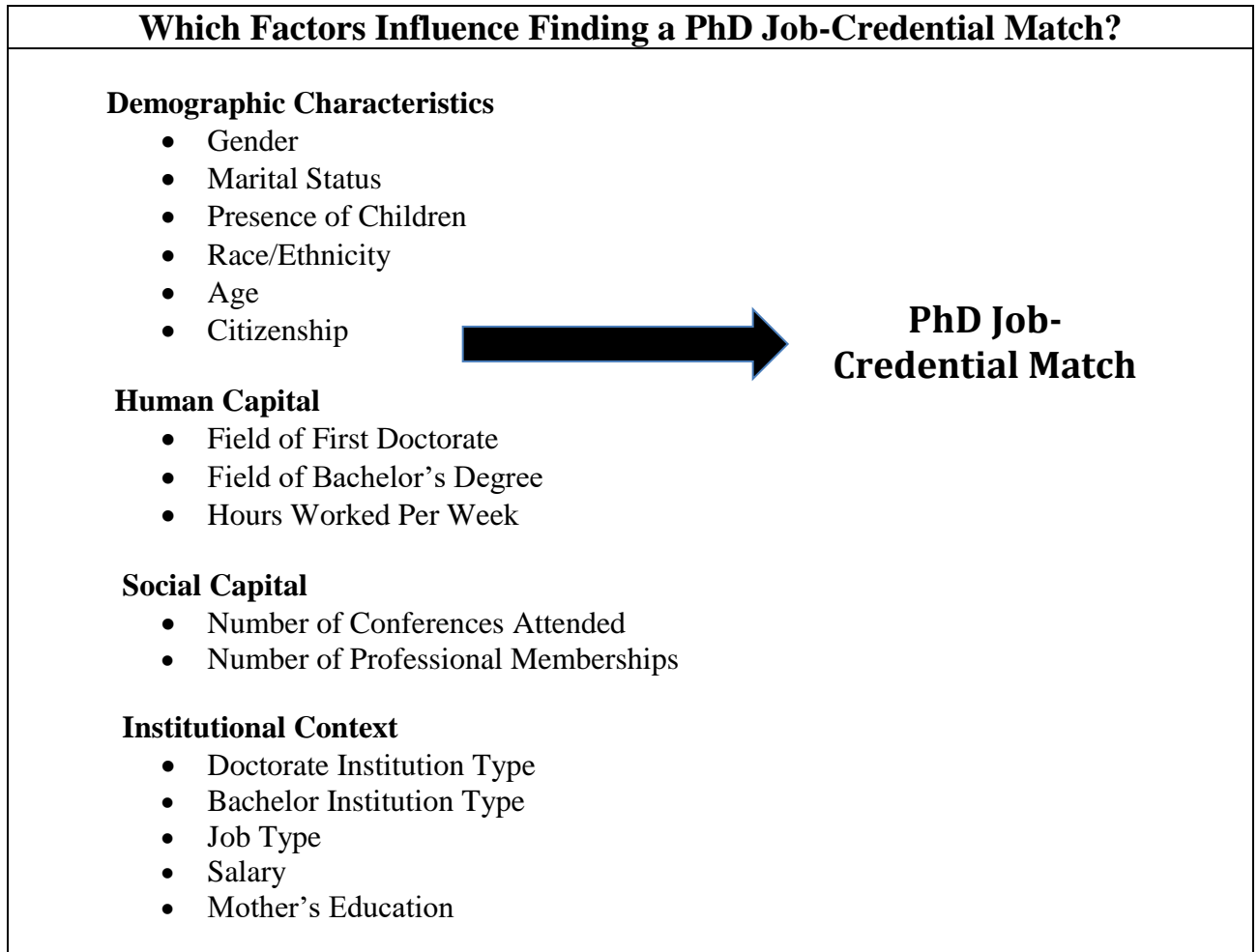


Figure 1: Conceptual Model

Demographic Characteristics

Demographic characteristics, such as age, gender, marital status, citizenship and the presence of children can provide more or fewer opportunities and choices based upon the social value or meaning of each characteristics. Women, for example, face systematic obstacles in finding the right educational job type and fit. Persistent gender stratification leads to systemic discrimination in hiring and promotion, and women's exclusion from high-status occupations or positions is more likely (Jaschik 2017). Once on the job, women in workplaces or occupations dominated by men typically face greater risks of

marginalization, tokenism, and “glass ceilings” (Bird and Rhoton 2011; Fitzsimons 2017; Irvine and Vermilya 2010).

Men, on the other hand, are systematically offered more opportunities. Studies show that men in occupations dominated by women quickly move into separate, often higher status, tracks (e.g., promotion into administration, management), and are actively “doing gender” in ways that facilitate boundary-building between their own work and that of their women colleagues (Budig 2002; Williams 1995). This shows how men are systematically given higher human capital and tracked into certain institutions, though this tracking is not necessarily an accurate representation of skills and abilities. At the PhD level, individuals can spend between 5 and 10 years earning their PhD (Zhou and Okahana 2019). If a PhD recipient is unable to find a job due to socially stratified systems (e.g. inequality regimes) surrounding one’s socially constructed demographics (e.g. race, gender), then the time and resources the PhD recipient invests in earning their degree is vexing and whole fields will lose intellectual capital.

Marital status and the presence of children are two additional key demographic characteristics that could influence job options. One study found that in a sample of dual-income heterosexual couples, wives are less likely than their husbands to relocate for a better job if their husband will suffer a decrease in income (Bielby and Bielby 1992). For women in dual-earner families and who have children, there continues to be asymmetry of gender roles. Mothers average 13 more hours of housework and 6 more hours of childcare than fathers (Bianchi, Robinson, and Milkie 2007). This second shift women experience in childcare will not only impact the jobs available to them, but also the *type*

of job women (i.e. flexible hours) seek. In one study of college graduates on the east coast, men had a 52-mile larger job search radius than women (Kolmar, 2018).

Another salient demographic characteristic that could be associated with a PhD credential–job match is citizenship status. Often, international students come to the United States for a specific educational goal and are recruited into high-skilled jobs upon degree completion (Redden 2018). Although international students studying in the US are currently declining in number (Redden 2018), the act of moving to a new country to study and work in a specific field would presumably increase the potential for a PhD credential match. In light of the extant empirical research discussed above, I formulate the following hypotheses.

Hypotheses

H1a: I hypothesize that men scientists will have a greater likelihood of a job credential match than women scientists.

H1b: I hypothesize that scientists who are married will be less likely to have a match than scientists who are not married, as a partner and their partner's career could limit an individual's job options.

H1c: I hypothesize that scientists who live with children will be less likely to have a match than those who do not live with children.

H1d: Similar to H1a, I hypothesize that minorities will be less likely to have a job credential match than non-minorities, as they are subject to similar social constraints as women.

H1e: I predict older scientists will be more likely to have a job credential match than younger scientists, as they will have accrued more human and social capital and will have more leverage in finding a job with the right fit.

H1f: I predict non-U.S. citizens will be more likely to have a job credential match than native or naturalized U.S. citizens.

Human Capital

In light of its widespread use, it is important to consider Human Capital Theory as one (but not the sole) explanation in assessing the distribution of PhD earners in the labor market. In this thesis, human capital is measured in terms of the degree field (e.g. the broad and specialty field of bachelor and doctorate field of study) and number of hours worked per week (as a proxy for “commitment” to the job).

Because of differential supply and demand for positions across STEM PhD fields of study (Landivar 2013), I anticipate that there will be differences in whether an individual has a job that matches their PhD level degree field. In particular, because there are more jobs in the areas of computer and mathematical science and engineering in the science and engineering workforce (National Science Board 2018), I anticipate that recipients of doctoral degrees in these areas will be the most likely to have a job in-field. Given that a doctorate degree is sought to obtain in-depth knowledge in a topic (Bowen and Rudenstine 2014) and is more proximal in time to the current job because it is obtained after a bachelor’s degree, I anticipate that the doctorate field of study will be a stronger predictor of having a job-credential match than the bachelor’s degree field. Because I am using the number of hours per week as a proxy for commitment, I anticipate that those

who show the most “commitment” (work more hours per week) will be more likely to have a degree field-job match.

Hypotheses

H2a: I hypothesize that the field of first doctorate will be highly associated with a job-credential match.

H2b: I hypothesize that the field of an individual’s bachelor’s degree will not be associated with a job-credential match.

H2c: I hypothesize that the more hours an individual works per week, the greater likelihood a scientist will have a job-credential match

Social Capital

Social capital is another form of capital that plays a role in securing a job (Bozeman et al. 2001; Corley et al. 2019). As such, I include measures of social capital (e.g. network associations through professional memberships and conference attendance) to more thoroughly pinpoint the specific mechanisms that are associated with credential matches. This will also help to disentangle human capital from social capital.

Occupational networks are often demographically homogeneous (Ma 2011; Yoder 2017) but networking can help circumvent this homogeneity. In attending conferences and becoming members of professional groups, PhD-level professionals develop social capital and improve their job market standing – and potentially have a better opportunity for a credential match. Social capital is particularly advantageous for people seeking careers (Adler and Kwon 2002; de Janasz and Forret 2008). By networking within a field, an individual will gain access to network knowledge, resources, and mentorship, which is directly related to salary, promotions and career satisfaction (Seibert, Kraimer, and Liden

2001). Granovetter found that personal contacts as a source of network knowledge were related to higher income (Granovetter 2018). The association could also work in the other direction. Perhaps people with a degree-field match will be more professionally engaged and thus more likely to attend conferences and take part in professional memberships.

Hypotheses

H3a: I hypothesize that if a respondent attended a conference within the past year, they are more likely to have a job-credential match.

H3b: I hypothesize that the higher the number of professional memberships in which a scientist takes part, the more likely they will have a job-credential match.

Controlling for Institutional Context

Institutional level structures in higher education shape the lives of individuals and their social interactions that then lead to occupational inequalities (Acker 2006). Previous research has shown that institutional level factors can influence gender differences in undergraduate student outcomes (DeAngelo 2011, Carnegie Foundation 2018). For example, the undergraduate gender gap between male and female GPA is greater at non-Research I institutions than at non-Research I institutions (Bender and Heywood 2011; Yoder 2017). Similarly, undergraduate students attending colleges that spend more on research expenditures and comparatively less on the educational experience of the student body are less likely to persist in STEM majors (Griffith 2010).

Because educational institutions are a direct pathway into jobs, the type of institution at both the collegiate and doctoral level could make a difference in a credential match. Due to the importance of institutional context, this thesis will incorporate

institutional variables (e.g. the Carnegie classification of the scientists' bachelor and doctoral institutions) as control variables.

Much of the current research on credential-job matches relies more heavily on job duties and tasks over field of study. While the data used for this analysis does not provide specific occupational codes (or job tasks), it provides invaluable information regarding broad occupational categories. Specifically, the data identify classic research/academic jobs as separate from managerial roles and teaching roles. Because this data will allow for an exploration of job field *and* specific job tasks, I'll take advantage of this measure and explore how each of my independent variables (demographic characteristics, human and social capital) are associated with having non-field specific managerial and teaching roles versus S&E jobs in-field and other non-S&E jobs.

DATA AND METHODS

Data Source and Sample

The *Survey of Doctorate Recipients (SDR)* is a biennial survey conducted by the National Center for Science and Engineering Statistics (NCSES) within the National Science Foundation for individuals who hold a doctorate degree in a broad range of STEM fields. These STEM fields also include health-related sciences and are often referred to as "Science, Engineering or Health: (SEH) fields. This survey asks about demographic information (age, race, sex, ethnicity, citizenship, marital and parental status), educational history, field of degree and occupational information of the doctorate degree earner, as well as spousal occupational information. The *Survey of Doctoral Recipients* has been conducted since 1973. The objectives of the survey are twofold: to

identify consistent estimates of employment outcomes and to maintain parity within demographic characteristics (such as gender, race and disability) parity in SEH fields (National Science Foundation, 2019).

The sample frame of this study is created from the annual Survey of Earned Doctorates (SED), a census of all U.S. research doctoral degree recipients. The population size of SEH research doctorate degrees in 2015 is approximately 1,047,900, and the number of individuals sampled in the 2015 survey approximated 120,000 individuals. The individuals sampled the first week of February 2015 had earned a SEH research doctorate degree from a U.S. academic institution prior to July 2013. Respondents in this sample were less than 76 years of age, and not institutionalized nor terminally ill as of February 1st, 2015. The SDR uses a fixed panel design. A sample of new doctoral recipients are added to the panel during each survey cycle. The new sample for the 2015 SDR was selected using a stratified sample, where the strata are defined by the 2013 SED fields of study. This 2015 sample possesses an oversample of individuals included in the 2013 SDR, underrepresented minorities in the doctorate population and women.

The *Survey of Doctorate Recipients* collects its data through a trimodal approach: a self-administered questionnaire sent in the mail, a self-administered online survey and a computer-assisted telephone interview (CATI). In the 2015 SDR, the weighted response rate was 66%, while the unweighted response rate was 68%. The SDR includes sampling weights for each survey respondent in order to create unbiased population estimates and account for nonresponse bias. The analysis weights used in the data account for differential sampling rates, adjustments for unknown eligibility, adjustments for

nonresponse and adjustments to align with the Doctorate Records File (DRF) distribution on gender, race and ethnicity, degree year and degree field. The SDR data included both logical imputation and statistical (hot deck) imputation in its data processing. A hot deck imputation method was utilized for item nonresponse. In order to reduce over-coverage, the SED is compared and evaluated against the SDR reported information, and weights are developed to bring the SDR respondents in line with the SED population.

Table 1: Descriptive Statistics, Including Gender Differences, by Percentage

| | Total | Women | Men | F Test for Differences Across Men & Women |
|------------------------------------|----------|----------|----------|---|
| | N=63,635 | N=29,075 | N=43,664 | |
| <i>Dependent Variables</i> | | | | |
| Broad Field Match | 60.98% | 61.66% | 60.65% | 3.28 |
| Specialty Field Match | 55.77% | 57.36% | 55.05% | 15.76*** |
| Specialty Field Match by Job Type | | | | |
| Mismatch (Known) | 27.03% | 25.84% | 27.58% | |
| Match | 55.25% | 56.42% | 54.71% | |
| Teacher | 14.30% | 4.91% | 2.73% | |
| Manager | 3.42% | 12.83% | 14.97% | 46.59**** |
| <i>Demographic Characteristics</i> | | | | |
| Gender | | 32.62% | 67.38% | |
| Marital Status | | | | |
| Not Married | 20.66% | 30.08% | 16.10% | 1018.85**** |
| Married | 79.34% | 69.92% | 83.90% | |
| Living with Children | | | | |
| Not Living with Children | 63.55% | 63.51% | 63.57% | 0.01 |
| Living with Children | 36.45% | 36.49% | 36.43% | |
| Minority | | | | |
| No | 91.16% | 89.03% | 92.19% | 178.65**** |
| Yes | 8.84% | 10.97% | 7.81% | |
| Age (Years) | | | | |
| 29 or younger | 0.77% | 1.00% | 0.65% | |
| 20-34 | 8.35% | 10.96% | 7.08% | |
| 35-39 | 12.31% | 15.41% | 10.81% | |
| 40-44 | 12.10% | 14.16% | 11.10% | |
| 45-49 | 11.62% | 12.45% | 11.21% | |
| 50-54 | 12.12% | 11.47% | 12.44% | |
| 55-59 | 11.31% | 10.64% | 11.63% | |
| 60-64 | 11.38% | 10.24% | 11.93% | |
| 65-69 | 10.27% | 8.16% | 11.30% | |
| 70-75 | 9.78% | 5.51% | 11.85% | 98.90**** |

| | | 100.00% | 100.00% | | |
|-----------------------------------|--|--------------|------------|--|------------|
| | Total | Women | Men | F Test for Differences Across Men & Women | |
| | US Citizen, Native | 62.63% | 68.48% | 59.80% | |
| | US Citizen, Naturalized | 17.15% | 14.95% | 18.21% | |
| | Non-US Citizen | 20.22% | 16.57% | 21.98% | 138.68**** |
| <i>Social & Human Capital</i> | | | | | |
| | Field of First Doctorate | | | | |
| | Computer and Mathematical Sciences | 8.35% | 5.51% | 9.63% | |
| | Biology, Agricultural and Environmental Sciences | 25.87% | 32.05% | 23.06% | |
| | Physical and Related Sciences | 17.83% | 11.77% | 20.57% | |
| | Social and Related Sciences | 27.83% | 41.62% | 21.58% | |
| | Engineering | 20.13% | 9.05% | 25.15% | 814.42**** |
| | Field of Bachelor's Degree | | | | |
| | Computer and Mathematical Sciences | 7.64% | 5.48% | 8.69% | |
| | Biology, Agricultural and Environmental Sciences | 20.45% | 24.90% | 18.29% | |
| | Physical and Related Sciences | 19.03% | 12.84% | 22.02% | |
| | Social and Related Sciences | 20.17% | 28.65% | 16.07% | |
| | Engineering | 19.87% | 8.11% | 25.56% | |
| | S&E Related Fields | 4.29% | 8.01% | 2.49% | |
| | Non-S&E Related Fields | 7.16% | 10.83% | 5.38% | |
| | Logical Skip | 1.39% | 1.18% | 1.50% | 520.79**** |
| | Attended Conferences In the Past Year | | | | |
| | No | 38.53% | 37.52% | 39.03% | |
| | Yes | 61.43% | 62.45% | 60.94% | 4.99** |
| | Number of Professional Memberships | | | | |
| | 0 | 29.11% | 28.75% | 29.28% | |
| | 1 | 22.03% | 21.00% | 22.52% | |
| | 2 | 21.36% | 21.47% | 21.31% | |
| | 3 | 13.96% | 14.47% | 13.72% | |
| | 4+ | 13.50% | 14.27% | 13.13% | 4.71**** |
| | Hours Per Week Typically Worked | | | | |
| | Less than 20 | 5.13% | 6.70% | 4.38% | |
| | 21-35 | 6.10% | 8.46% | 4.95% | |
| | 36-40 | 25.98% | 25.42% | 26.26% | |
| | 40+ | 49.14% | 46.27% | 50.53% | 71.77**** |
| <i>Controls</i> | | | | | |
| | Doctorate Institution Type | | | | |
| | Publicly Controlled | 68.77% | 67.77% | 69.26% | |
| | Privately Controlled | 31.14% | 32.10% | 30.67% | |
| | Bachelor Institution Type | | | | |
| | Publicly Controlled | 38.51% | 41.05% | 37.28% | |
| | Privately Controlled | 29.40% | 33.12% | 27.59% | |
| | Logical Skip | 1.39% | 1.18% | 1.50% | |
| | Info Not Available, likely Foreign Institution | 30.71% | 24.65% | 33.64% | 118.67**** |
| | Job Type | | | | |
| | Academic | 41.16% | 44.93% | 39.33% | |
| | Government | 7.71% | 8.05% | 7.54% | |

| | Business | 37.49% | 33.87% | 39.23% | 46.30**** |
|--------------------|---|--------------|--------------|------------|--|
| | | Total | Women | Men | F Test for Differences Across Men & Women |
| Salary | | | | | |
| | \$0-65,000 | 24.74% | 31.45% | 21.46% | |
| | \$65,000-100,000 | 25.43% | 31.10% | 22.66% | |
| | \$100,000-160,000 | 32.16% | 27.06% | 34.65% | |
| | \$160,000-511,000 | 17.67% | 10.39% | 21.23% | 382.74**** |
| Mother's Education | | | | | |
| | Less than HS | 15.62% | 10.40% | 18.15% | |
| | HS Degree | 26.83% | 24.15% | 28.13% | |
| | Some College | 17.06% | 18.83% | 16.21% | |
| | College Degree | 22.04% | 24.50% | 20.85% | |
| | Master's | 13.14% | 15.29% | 12.10% | |
| | Professional Degree | 2.45% | 3.26% | 2.07% | |
| | Doctorate | 2.65% | 3.43% | 2.28% | |
| | Not Applicable (e.g. single parent household) | 0.20% | 0.15% | 0.23% | 93.81**** |

+p<.10, *p<.05, **p<.01, ***p<.001, ****p<.0001

Measures

Dependent Variables

The primary dependent variable used in this analysis is looking at the binary match or mismatch between the respondent's principal job and principal field of study for their doctorate. The survey differentiates six broad STEM jobs and broad field of study categories: 1. Computer and Mathematical Sciences, 2. Biology, Agricultural and Environmental Life Sciences, 3. Physical and Related Sciences, 4. Social and Related Sciences, 5. Engineering, and 6. Science & Engineering Related Fields. The principal or "broad" fields of study are a summary of the subfields that STEM PhD recipients can enter, and defined by the NSF on the data file. I create a dichotomous dependent variable indicating that there is a "match" between the field for the principal job (defined using the variable "broad field of doctorate" and the principal field of study for the PhD (defined using the variable "principal job"). This variable takes the value of 1 where the

broad field of study for the PhD and the broad field for the respondent's principal job match (e.g., both the job and the PhD are in the Social and Related Sciences) and a value of 0 where the broad field of study for the PhD and the broad field for the respondent's principal job do not match (e.g., the job is in Biology, Agriculture, and Environmental Life Sciences and the PhD is in Social and Related Sciences.) Unemployed or retired individuals are set equal to missing. Overall, 60.98% of the respondents have a job that matches their field of study for the PhD. Out of the women respondents, 61.98% are in a broad field match, and of the men respondents, 60.65% are in a broad field match.

In order to take into account the more nuanced types of fields of study, I also compare the match/mismatch with the respondent's specialty field of study and specialized job match/mismatch. *Specialty fields of study* include a more complex typology of the fields STEM PhD students can study or enter. The categories for specialty field of study for the PhD include Computer and Information Sciences, Mathematics and Statistics, Agricultural and Food Sciences, Biological Sciences, Environmental Life Sciences, Chemistry, Except Biochemistry, Earth, Atmospheric and Ocean Sciences, Physics and Astronomy, Other Physical Sciences, Economics, Political and Related Sciences, Psychology, Sociology and Anthropology, Other Social Sciences, Aerospace, Aeronautical and Astronautical Engineering, Chemical Engineering, Civil and Architectural Engineering, Electrical and Computer Engineering, Industrial Engineering, Mechanical Engineering, and Other Engineering. The categories for *specialty field for the principal job* include Computer and Information Scientists, Mathematical Scientists, Postsecondary Teachers – Computer and Math Sciences, Agricultural and Food Scientists, Biological and Medical Scientists, Environmental Life

Scientists, Postsecondary Teachers – Life and Related Sciences, Chemists, Except Biochemists, Earth Scientists, Geologists and Oceanographers, Physicists and Astronomers, Other Physical and Related Scientists, Postsecondary Teachers – Physical and Related Sciences, Economists, Political Scientists, Psychologists, Sociologists and Anthropologists, Other Social and Related Scientists, Postsecondary Teachers – Social and Related Sciences, Aerospace, Aeronautical or Astronautical Engineers, Chemical Engineers, Civil, Architectural or Sanitary Engineers, Electrical or Computer Hardware Engineers, Industrial Engineers, Mechanical Engineers, Other Engineers, Postsecondary Teachers – Engineering, Health-Related Occupations, Science & Engineering Managers, Science & Engineering Pre-College Teachers, Science & Engineering Technicians and Technologists, Other S&E Related Occupations, Non-S&E Managers, Management-Related Occupations, Non-S&E Precollege Teachers, Non-Science & Engineering Postsecondary Teachers, Social Services and Related Occupations, Sales & Marketing Occupations, Art, Humanities & Related Occupations, Other non-Science & Engineering Occupations.

I create a dichotomous dependent variable indicating that there is a “match” between the specialty field for the principal job (defined using the variable “job of specialty field”) and the principal specialty field of study for the PhD (defined using the variable “specialty field of doctorate”). This variable takes the value of 1 where the specialty field of study for the PhD and the fine field for the respondents’ principal job match (e.g., both the job and the PhD. are in Computer and Information Sciences) and a value of 0 where the specialty field of study for the PhD and the specialty field for the respondent’s principal job do not match (e.g., the job is in Chemical Engineering and the

PhD is in Electrical or Computer Hardware Engineering). Overall, 55.77% of the respondents have a job that matches their specialty field of study for the PhD 57.36% of women and 55.05% of men have a job that matches their specialty field of PhD study.

These specialty field categories help pinpoint specific (mis)match dynamics that remain invisible when we only examine broad field of study. By looking closer at the specialty field of study, I parse out the teaching and management jobs that cannot easily be matched with the many specialty fields of study (Appendix A). In particular, the specialty field for the principal job include all persons whose primary job is “teaching” or “administration” in the postsecondary teaching and manager categories. Thus, even if those individuals identify themselves as scientists who are working in their field, their principal job fails to categorize them accordingly (e.g., a university College Dean who continues to do research in their field of study would be classified as an administrator and thus working out-of-field according to the specialty field of study). This leads to the creation of a four category dependent variable which takes the value of 0 for being a known specialty field mismatch, 1 for known specialty field match, 3 for a job as a teacher with no clear field designation, and 4 for a job as a manager/administrator with no clear field designation. Overall, 27.03% of employed PhD scientists are in a field with a known mismatch between the specialty field of job and the field for the PhD, 55.25% have a known match between the specialty field of job and the field for the PhD, 14.30% are employed as teachers with an unknown field of employment, and 3.42% are employed as managers with an unknown field for the job. Among women, 25.84% of them have a known mismatch between specialty field of study and specialty field of job, 56.42% of women have a specialty field match, 4.91% of women are teachers and

12.83% of women are managers. The breakdown for men is that 27.58% are in a specialty field mismatch, 54.71% are in a specialty field match, 2.73% are teachers and 14.97% of men are managers.

Independent Variables

Sixteen independent variables are used in this analysis, grouped under the following three categories: a) *demographics*, b) *social and human capital*, and c) *control variables*. Table 1 contains the overall descriptive statistics for each independent variable, including distributions for men and women.

For *demographic* variables, I include six indicators. The gender of the respondent is a dichotomous variable of male (=0, 67.38%) and female (=1, 32.62%). The marital status of respondent was collected as a six category variable asking “On February 1, 2015 were you: 1: Married, 2: Living in a marriage-like relationship, 3: Widowed, 4: Separated, 5: Divorced, or 6: Never Married. I recoded marital status into two categories, married (=1, 79.34%) versus not married (=0, 20.66%); 30.08% of women are not married and 16.10% of men were not married. Presence of children under the age of 18 in the household was collected as a two category variable asking, “As of the week of February 1, 2015, did you have any children living with you as part of your family?”, This question was recoded into a dichotomous variable of not living with children (=0, 63.55%) versus living with children (=1, 36.45%). 63.51% of women and 63.57% of men do not live with children, indicating no gender difference. Minority status of respondents was collected as a two category combination of a five category race and ethnicity variable. The race and ethnicity variable categories included Asian non-Hispanic, Black non-Hispanic, Hispanic, White non-Hispanic and Other Underrepresented minorities. The

minority status indicator variable combined these categories into being a minority (Black, non-Hispanic, Hispanic and underrepresented minorities) or not a minority (e.g. Asian, non-Hispanic and White, non-Hispanic). I recoded the minority status indicator variable into a dichotomous variable of not a minority (=0, 91.16%) versus a minority (=1, 8.84%); 10.97% of women were minorities and 7.81% of men were minorities. Age of respondent was coded as a ten category variable of age ranges: 29 or younger (0.77%) (women: 1.00%, men: 0.65%), 20-34 years old (8.35%) (women: 10.96%; men: 7.08%), 35-39 years old (12.31%) (women: 15.41%, 10.81%), 40-44 years old (12.10%) (women: 14.16%; men: 11.10%), 45-59 years old (11.62%) (women: 12.45%; men: 11.21%), 50-54 years old (12.12%) (women: 11.47%; men: 12.44%), 55-59 years old (11.31%) (women: 10.64%; men: 11.63%), 60-64 years old (11.38%) (women: 10.24%; men: 11.93%), 65-69 years old (10.27%) (women: 8.16%; men: 11.30%), and 70-75 years old (9.78%) (women: 5.51%; men: 11.85%). Citizenship status of the respondent was collected as a five category variable: 1. U.S. citizen, Native, 2. U.S. citizen, Naturalized, 3. Non-U.S. citizen, Permanent resident, 4. Non-U.S. citizen, Temporary resident, 5. Non-U.S. citizen, living outside the U.S. I recoded the five category citizenship variable to a three category variable, U.S. Citizen, Native (=1, 62.63%) (women: 68.48%; men: 59.80%), U.S. Citizen, Naturalized (=2, 17.15%) (women: 14.95%; men: 18.21%) and Non-U.S. Citizen (=3, 20.22%) (women: 16.57%; men: 21.98%).

To measure *social and human capital*, I use five indicators. The broad field of study for a doctoral degree is a seven-category variable asking field of study for highest degree (broad field). These categories include: 1. Computer and Mathematical Sciences (8.35%) (women: 5.51%; men: 9.63%), 2. Biology, Agricultural and Environmental

Sciences (25.87%) (women: 32.05%; men: 23.06%), 3. Physical and Related Sciences (17.83%) (women: 11.77%; men: 20.57%), 4. Social and Related Sciences (27.83%) (women: 41.62%; men 21.58%) and 5. Engineering (20.13%) (women: 9.05%; men: 25.15%).

I kept these categories but dropped S&E Related Fields and Non S&E Related Fields. For S&E Related Fields, there weren't clear matches with the specialty field of study, and S&E Related Fields only had 7 people in this category. The top three most common PhD fields are Social and Related Sciences (27.83%), Biology, Agricultural and Environment Sciences (25.87%) and Engineering (20.13%).

The broad field of study for bachelor's degree (major group) is an eight-category variable asking for field of study for first bachelor's degree (major group). I retained these eight broad categories: 1. Computer and Mathematical Sciences (7.64%) (women: 5.48%; men: 8.69%), 2. Biology, Agricultural and Environmental Sciences (20.45%) (women: 24.90%; men: 18.29%), 3. Physical and Related Sciences (19.03%) (women: 12.84%; men: 22.02%), 4. Social and Related Sciences (20.17%) (women: 28.65%; men: 16.07%), 5. Engineering (19.87%) (women: 8.11%; men: 25.56%), 6. Science and Engineering Related Fields (4.29%) (women: 8.01%; men: 2.49%), 7. Non-Science and Engineering Related Fields (7.16%) (women: 10.83%; men: 5.38%) and 8. Logical Skip (1.39%) (women: 1.18%; men: 1.50%). The Logical Skip category is presumably the scientists who skipped earning their undergraduate degree and went directly to earn their masters or PhD. The top four most common bachelor's degree types mirror the PhD level distributions: Biology, Agricultural and Environmental Sciences (20.45%), Social and

Related Sciences (20.17%), Engineering (19.87%) and Physical and Related Sciences (19.03%).

Attendance at professional conferences was collected as a two category variable asking, “During the past 12 months, did you attend any professional society or association meetings or professional conferences?” which I recoded into a dichotomous variable of no (=0, 38.53%) and yes (=1, 61.43%). 62.45% of women and 60.94% of men attended professional conferences within the past year. Professional group membership was collected as an eight category variable asking, “Number of Professional Society Memberships.” These categories include: No memberships, 1 membership, 2 memberships, 3 memberships, 4 memberships, 5 memberships, 6 or more memberships and Logical Skip. I collapsed the 4, 5 and 6 or more membership categories into one. I set the Logical Skip category (n=34) to missing. My final categories for this variable include: 0 memberships (29.11%) (women: 28.75%; 29.28%), 1 membership (22.03%) (women: 21%; men: 22.52%), 2 memberships (21.36%) (women: 21.47%; men: 21.31%), 3 memberships (13.96%) (women: 14.47%; men: 13.72%) and 4 or more memberships (13.50%) (women: 14.27%; men: 13.13%). Finally, number of work hours was collected as a five category variable asking, “Principal job: hours per week typically worked?” These categories include 20 hours or less (5.13%) (women: 6.70%; men: 4.38%), 21-35 hours (6.10%) (women: 8.46%; men: 4.95%), 36-40 hours (25.98%) (women: 25.42%; men: 26.26%), greater than 40 (49.14%) (women: 46.27%; men: 50.53%) and logical skip (13.65%) (women: 13.15%; men: 13.89%), which I retained.

I measure 5 *control* variables in this study. Carnegie classification of the doctoral granting institution was measured as a three-category variable asking, “From which

academic institution did you receive your highest degree (1994 Public/Private flag)? I kept the three categories NSF recorded: Publicly Controlled (68.77%) (women: 67.77%; men: 69.26%), Privately Controlled (31.14%) (women: 32.10%; men: 30.67%) and Info Not Available (0.087%) (women: 0.12%; men: 0.07%). The majority of respondents (68.77%) earned their doctorate at a publicly controlled institution. The Carnegie classification of the institution awarding the bachelor's degree was coded into four categories. This question asked. "From which academic institution did you receive your first BA degree (1994 Public/Private flag)?" I kept these four NSF recorded categories: Publicly Controlled (38.51%) (women: 41.05%; men: 37.28%), Privately Controlled (29.40%) (women: 33.12%; men: 27.59%), Logical Skip (1.39%) (women: 1.18%; men: 1.50%) and Information Not Available (30.71%) (women: 24.65%; men: 33.64%). Only 38.51% of respondents earned their bachelor's degree at a publicly controlled institution, but information was not available on 30.71% of respondent's bachelor educational credentials.

Job type was measured as a four-category variable asking which employment sector the respondent worked in during the week of February 1, 2015. I kept the categories NSF recorded: Educational Institution (e.g. Academic) (41.16%) (women: 44.93%; men: 39.33%), Government (7.71%) (women: 8.05%; men: 7.54%), Business/Industry (e.g. Business) (37.49%) (women: 33.87%; men: 39.23%) and Logical Skip (13.65%) (women: 13.15%; men: 13.89%). (This Logical Skip category encompasses respondents who are either retired, on layoff from a job, students, those with family responsibility, those who possess a chronic illness or permanent disability, a suitable job was not available or the respondent did not need or want to work. This

category was set equal to missing in the multivariate analyses.) 41.16% of respondents enter the academic sector, with 37.49% entering the business sector. Only 7.71% of respondents work for the government.

Salary was a quasi-continuous variable category variable ranging from \$0 to \$511,000. These original categories had a \$1000 gradation between them from \$0 to \$347,000. The last two categories were \$511,000 and a logical skip. Because of these categories, I divided up the distribution of salaries into quartiles. Quartile one consists of earners between \$1,000 and \$64,999 (24.74%) (women: 31.45%; men: 21.46%), quartile two consists of earners between \$65,000 and \$99,999 (25.43%) (women: 31.10%; men: 22.66%), quartile three consists of earners between \$100,000 and \$159,999 (32.16%) (women: 27.06%; men: 34.65%) and quartile four consists of earners between \$160,000 and \$511,000 (17.67%) (women: 10.39%; men: 21.23%). I dropped the logical skips from the analysis.

Mother's education was measured as a nine category variable. The last category was set to missing, which I dropped. My final categories, which I retained from the NSF categorization are: 1. Less than high school completed (15.62%) (women: 10.40%; men: 18.15%), 2. High school diploma or equivalent (26.83%) (women: 24.15%; men: 28.13%), 3. Some college, vocational, or trade school (including 2-year degrees) (17.06%) (women: 18.83%; men: 16.21%), 4. Bachelors degree (e.g. BS, BA, AB) (22.04%) (women: 24.50%; men: 20.85%), 5. Masters degree (e.g. MS, MA, MBA) (13.14%) (women: 15.29%; men: 12.10%), 6. Professional degree (e.g. JD, LLB, MD, DDS, etc.) (2.45%) (women: 3.26%; men: 2.07%), 7. Doctorate (e.g. PhD, DSc, EdD,

etc.) (2.65%) (women: 3.43%; men: 2.28%), and 8. Not applicable (0.20%) (women: 0.15%; men: 0.23%).

Analytic Strategy

All of my analyses account for unequal selection probabilities and nonresponse adjustments using the svy commands in Stata. There are no variables for clusters or strata in the public use dataset.

My analytic strategy has four steps. First, I examine whether the independent variables vary for men and women. This analysis establishes if the difference between men and women is statistically significant. I use survey-design adjusted chi-square statistics that have been transformed into F-statistics (SDR, 2015) to evaluate whether the distribution of the demographics, human capital indicators, social capital indicators, and control variables vary for men and women.

Second, I examine the bivariate association between my independent variables and the dependent variables of matches with the broad and specialty fields of study. I test whether the distribution of a PhD scientist having a job that matches their broad or specialty field of study varies across categories of my independent variable using survey-design adjusted F-statistics.

Third, I use survey-design adjusted logistic regression models to assess the association between demographic characteristics and the possession of human and social capital with my outcome variables. I estimate a series of three models for each dependent variable. In the first set of models, I include demographic characteristics. Then, I add the proxy measures for human and social capital. Finally, I add the control variables to the model.

Fourth, by looking closer at the specialty field, I parse out the teaching and managing jobs that cannot easily be matched with the many specialty fields of study (Table 4). I use survey-design adjusted multinomial regression models to assess the association between demographic characteristics and the possession of human and social capital with being either a manager in a non-specific field or a teacher in a non-specific field. I estimate one full model to include the independent variables.

RESULTS

Descriptive Statistics

Table 1 shows the distribution of the variables of interest for the full sample and separately for men and women. Approximately 40% of men and women find jobs outside of their principal doctorate field of study, with no meaningful difference between men and women. When I examine the specialty field of study, this loose coupling increases as 44% of men and women find jobs outside of their minor specialty field, with slight differences between men (55.05% in field) and women (57.36% in field $p < .05$). By looking closer at the specialty field, I parse out the teaching and managing jobs that cannot easily be matched with the many specialty fields of study. Looking at the type of position for each respondent, Table 1 shows that 14.30% of PhD scientists are employed in post-secondary teaching positions that are not directly related to their degree field, and 3.42% are employed in administrative or management positions. There are notable differences in these types of jobs for men and women – 4.91% of women compared to 2.73% of men enter non-field specific post-secondary teaching positions, and 14.97% of men compared to 12.83% of women enter managerial positions. ($p < .0001$). These gender

differences in job type provide initial evidence of gender tracking for PhD level scientists.

I now examine whether the demographic measures of interest vary for men and women (second panel of Table 1). Most PhD STEM scientists are men (67.38%), and the majority of scientists are married (79.34%). The overwhelming majority of PhD STEM scientists are white, non-Hispanic only or Asian, non-Hispanic only, but there is a significant difference between men and women. Of the STEM PhD recipients who are women, 10.97% are minorities while 7.81% of STEM PhD recipients are men ($p < .0001$). There is a greater gender segregation of STEM PhD recipients between the ages of 35 and 69. Finally, 62.63% of respondents are native U.S. citizens.

Overall, 30% of women who possess a STEM doctorate are not married, compared to 16% of men ($p < .0001$). Specialty field match by job type is gendered. There is a higher percentage of women in teaching positions compared to men. Inversely, there is a higher percentage of men in managerial positions than women ($p < .0001$). The only age group in which women have earned more STEM PhDs than men are those between the ages of 45 and 49. There is a higher percentage of women who are native U.S. citizens (68.48%) as compared to men (59.80%), and more men are non-U.S. citizens (21.98%) than women (16.57%) ($p < .0001$).

I now examine the variables representing social and human capital. Men and women earn PhDs in different fields. Women are more likely than men to hold a PhD in the fields of Social and Related Sciences (41.62% of women compared to 21.58% of men) and Biology, Agricultural, and Environmental Sciences (32.05% vs. 23.06%). Men are more likely than women to hold a PhD in Engineering (25.15% compared to 9.05%),

Physical and Related Sciences (20.57% compared to 11.77%) and Computer and Mathematical Sciences (9.63% compared to 5.51%) ($p < .0001$).

Similarly, women are more likely to have earned a bachelor's degree in the Social and Related Sciences (with 28.65% of women compared to 16.07% earning this degree), Biology, Agricultural and Environmental Sciences (24.90% vs. 18.29%), and S&E related fields (with 8.01% of women and 2.49% of men earning this degree). Men are more likely than women to have earned a bachelor's degree in Engineering (25.56% compared to 8.11%), Physical and Related Sciences (22.02% compared to 12.84%) and Computer and Mathematical Sciences (8.69% compared to 5.48%) ($p < .0001$).

Women attend conferences more often than men ($p < .01$) and are more likely to work part time than full time ($p < .01$). 41.05% of women attended a public institution in their undergraduate career as compared to 37.28% of men ($p < .0001$). A large difference between men and women is their job type after earning their STEM PhD 44.93% of women are in academic work as compared to 39.33% of men, and 39.23% of men are working in the private business sector as compared to only 33.87% of women ($p < .0001$).

Although the overall salary distribution is in rough quartiles, there are clear gender differences in the distribution of salaries. More women than men earn between \$0 and \$100,000 for their annual salary and more men than women earn between \$100,000 and \$511,000 ($p < .0001$).

Bivariate Results

Table 2 contains bivariate results assessing the association between independent (demographic characteristics, social and human capital indicators) variables and dependent variables (broad and specialty field matches). For each independent variable, I

assess whether the independent variable is statistically associated with having a job that matches versus does not match with the PhD field of study using chi-square tests that have been transformed into survey-adjusted F-tests for distributional differences across the categories of each independent variable. For sake of parsimony, the table contains only the “matched” percentages; the “not matched” percentages can be calculated within each independent variable by taking 100 minus the matched percentages. Thus, the table can be interpreted as 61.66% of female scientists have a job that matches their broad field of study and 38.34% (100-61.66) do not. For variables with more than two categories, the statistical tests are the same, evaluating differences in distributions of the dependent variable (match versus not match) across categories of the independent variable. For example, 70.16% of scientists who are aged 29 or younger have a job that matches their broad field of study (and 29.84%=100-70.16 do not), with the percentage decreasing to 57.42% of scientists aged 70 to 75 having a job that matches their PhD field of study. Thus each analysis reflects a bivariate table of size $2*k$, where 2 is the number of categories in the dependent variable and k is the number of categories in the independent variable.

The bivariate results assessing broad field of study and broad field match and the results assessing specialty field of study and specialty field match were similar; therefore, both are presented in Table 2. Due to this similarity, I discuss the analyses of the specialty fields rather than the broad field matches. Also due to the large sample size, I only discuss differences that exceed 5 percentage points.

Table 2 Percentage of Respondents Who Have a Job/PhD Match in their Broad Field and Specialty Field by Demographic Characteristics, Social and Human Capital Characteristics, and Control Variables

| | | Match in Broad Field | F test for differences in broad field match within categories of the independent variables | Match in Specialty Field | F-test for differences in specialty field match within categories of the independent variables |
|------------------------------------|----------------------------|--|--|--------------------------------|---|
| | | N=63,645 | | N=63,640 | |
| <i>Demographic Characteristics</i> | | | | | |
| | Gender | | | | |
| | | Female | 61.66% | 57.36% | |
| | | Male | 60.65% | 55.05% | 15.76*** |
| | Marital Status | | | | |
| | | Married | 60.46% | 55.19% | |
| | | Not Married | 62.98% | 58.03% | 16.49***** |
| | Living with Children | | | | |
| | | Living with Children | 61.33% | 56.14% | |
| | | Not Living with Children | 60.76% | 55.52% | 1.10 |
| | Minority | | | | |
| | | No | 60.81% | 55.50% | |
| | | Yes | 62.69% | 58.45% | 14.90*** |
| | Age (Years) | | | | |
| | | 29 or younger | 70.16% | 64.60% | |
| | | 30-34 | 70.07% | 65.83% | |
| | | 35-39 | 65.67% | 60.40% | |
| | | 40-44 | 63.65% | 58.18% | |
| | | 45-49 | 57.43% | 51.75% | |
| | | 50-54 | 58.47% | 52.68% | |
| | | 55-59 | 59.20% | 53.13% | |
| | | 60-64 | 57.26% | 52.88% | |
| | | 65-69 | 56.94% | 52.40% | |
| | | 70-75 | 57.42% | 52.95% | 26.94***** |
| | Citizenship | | | | |
| | | US Citizen, Native | 60.20% | 55.58% | |
| | | US Citizen, Naturalized | 55.43% | 48.76% | |
| | | Non-US Citizen | 67.51% | 61.78% | 91.09***** |
| <i>Social & Human Capital</i> | | | | | |
| | Field of First Doctorate | | | | |
| | | Computer and Mathematical Sciences | 76.07% | 70.90% | |
| | | Biology, Agricultural and Environmental Sciences | 58.55% | 54.26% | |
| | | Physical and Related Sciences | 53.86% | 49.57% | |
| | | Social and Related Sciences | 64.35% | 61.17% | |
| | | Engineering | 60.37% | 49.28% | 126.74***** |
| | Field of Bachelor's Degree | | | | |
| | | Computer and Mathematical Sciences | 71.96% | 67.05% | |
| | | Biology, Agricultural and Environmental Sciences | 60.10% | 56.08% | |

| | Match in Broad Field | F test for differences in broad field match within categories of the independent variables | Match in Specialty Field | F-test for differences in specialty field match within categories of the independent variables |
|---|-------------------------|--|--------------------------------|--|
| Physical and Related Sciences | 54.09% | | 49.90% | |
| Social and Related Sciences | 67.81% | | 64.97% | |
| Engineering | 60.75% | | 50.65% | |
| S&E Related Fields | 57.44% | | 45.32% | |
| Non-S&E Related Fields | 53.49% | | 50.79% | |
| Logical Skip | 58.96% | 57.42**** | 51.17% | 73.64**** |
| Attended Conferences In the Past Year | | | | |
| No | 56.46% | | 50.03% | |
| Yes | 63.11% | 116.95**** | 58.53% | 119.56**** |
| Number of Professional Memberships | | | | |
| 0 | 53.71% | | 47.29% | |
| 1 | 63.88% | | 58.51% | |
| 2 | 62.19% | | 57.23% | |
| 3 | 64.80% | | 60.71% | |
| 4+ | 62.83% | 56.48**** | 58.74% | 73.04**** |
| Hours Per Week Typically Worked | | | | |
| Less than 20 | 58.00% | | 53.42% | |
| 21-35 | 63.71% | | 59.28% | |
| 36-40 | 64.02% | | 57.02% | |
| 40+ | 59.35% | 22.19**** | 54.92% | 7.94**** |
| <i>Controls</i> | | | | |
| Doctorate Institution Type | | | | |
| Publicly Controlled | 62.20% | | 56.65% | |
| Privately Controlled | 58.27% | | 53.80% | |
| Info Not Available, likely Foreign Institution | 79.30% | 26.97**** | 76.72% | 14.86**** |
| Bachelor Institution Type | | | | |
| Publicly Controlled | 60.60% | | 55.37% | |
| Privately Controlled | 58.89% | | 55.09% | |
| Logical Skip | 58.96% | | 51.17% | |
| Info Not Available | 63.36% | 13.40**** | 57.00% | 3.79* |
| Job Type | | | | |
| Academic | 71.24% | | 69.46% | |
| Government | 62.48% | | 52.76% | |
| Business | 49.42% | 701.75**** | 41.69% | 1038.09**** |
| Salary | | | | |
| \$0-65,000 | 65.73% | | 62.32% | |
| \$65,000- 100,000 | 70.11% | | 65.65% | |
| \$100,000-160,000 | 61.08% | | 54.31% | |
| \$160,000-511,000 | 41.04% | 404.14**** | 35.33% | 420.90**** |

| | Match in Broad Field | F test for differences in broad field match within categories of the independent variables | Match in Specialty Field | F-test for differences in specialty field match within categories of the independent variables |
|--|-------------------------|--|--------------------------------|---|
| Mother's Education | | | | |
| Less than HS | 60.97% | | 55.33% | |
| HS Degree | 61.01% | | 55.47% | |
| Some College | 60.30% | | 55.34% | |
| College Degree | 61.18% | | 56.09% | |
| Master's | 61.65% | | 56.68% | |
| Professional Degree | 59.77% | | 53.84% | |
| Doctorate | 60.28% | | 57.21% | |
| Not Applicable (e.g. single parent household) | 73.73% | 1.02 | 67.09% | 1.10 |

+p<.10, *p<.05, **p<.01, ***p<.001, ****p<.0001

Surprisingly, there were no gender differences in having a job that matched the broad field of study; when examining the specialty field of study, there were modest gender differences. For broad field of study, 61.66% of women and 60.65% of men had a job that matched their principal field. When looking at the specialty field of study, women were slightly more likely than men to have a job in their minor field, but this does not meet our differences greater than 5 percentage points criterion (55.05% of men vs. 57.36% of women, $p<.001$).

Now I look at the other demographic characteristics. Scientists with and without children were equally likely to have a job within their degree field (55.52% no children; 56.14% with children). Younger scientists were more likely to have a job in their specialty field than older scientists – roughly 60% of scientists under the age of 35 hold a job in their PhD area compared to only about 50% of scientists aged 45 and above. U.S.

citizens, either native (55.58%) or naturalized (48.76%), were less likely to have a job in their degree area than non-U.S. citizens (61.78%)

Next I look at social and human capital characteristics. Scientists who earn their doctoral degree in Computer and Mathematical Sciences (70.9%) are more likely to find a job in this field than scientists who earn a doctorate in Engineering (49.28%) or Physical and Related Sciences (49.57%). These findings are somewhat similar for scientists who earn their bachelor's degrees in these fields, as most science fields require undergraduate coursework to enter graduate school in this field.

Last I look at the control variables. For the Carnegie classification of the doctorate institution, scientists who come from doctoral institutions come from the small proportion of the sample that graduated from unidentified doctoral institutions (likely foreign institutions) (76.72%) are more likely to have a specialty field match than those from publicly controlled doctoral institutions (56.65%) and from privately controlled doctoral institutions (53.80%). The spread was more evenly distributed for scientists' bachelor's institution type, but the difference was significant. Scientists who come from undergraduate institutions for whom we do not have their Carnegie classification (57%) are more likely to find a specialty match than scientists from privately controlled undergraduate institutions (55.09%) and those from publicly controlled undergraduate institutions (53.37%). Scientists who enter the academic sector (69.46%) are more likely to be in their specialty field than those who work for the government (52.76%) or in the business sector (41.69%). Roughly 60% of scientists whose salary is between \$0 and \$100,000 is more likely to have a specialty match than scientists' whose salary falls

between \$100,000 and \$511,000. The education of the scientist's mother was not associated with finding a job specialty match.

Job Specialization

In this bivariate table, I parse out the job specialty matches even further. These analyses expand the previous specialty category mismatches into a four category dependent variable – those with a specialty PhD field that matches their job field, those with a known specialty PhD field that does not match their job field, those who teach in an unspecified field, and those who are managers in an unspecified field. Table 3 represents the distribution of respondents who are in specialty field matching, specialty field known non-matching, managerial, or teaching (non-field specific) roles. The statistical tests assessing the association between demographic characteristics, social and human capital indicators, and control variables with respondents who are in managerial or teaching positions again analyze a series of bivariate tables; here the bivariate tables are $4*k$, with four categories of the dependent variable and k categories for each independent variable.

Looking at the bivariate association between gender and the four category match and job type variable, I found gender differences within the specialized fields. Among men, 54.71% were in the same field as their doctorate degree, 27.58% are in a known S&E field that is not the same as their doctorate degree, 14.97% were in a managerial role and 2.73% were in a non-field specific teaching position. Women, on the other hand, differed, in that 56.42% were in the same field as their doctorate degree, 25.84% were in a known S&E field that is not the same as their doctorate degree, 12.83% of women were

in managerial positions and 4.91% were in a non-field specific teaching position. I note that again, none of these differences meet the five percentage point criterion.

Among the demographic characteristics, age and citizenship were significant indicators of job position. Scientists who are between the ages of 40 and 70 are less likely to be working in the field of their PhD and more likely to be in a managerial position than scientists who are younger than 40. Older scientists are also slightly more likely to go into post-secondary teaching positions than younger scientists. Native-born U.S. citizens (54.99%) are more likely to have a job that matches their field of study than naturalized U.S. citizens (46.89%), but both are less likely than non-U.S. citizens (48.30%) to have a job that matches their field of study. U.S. citizens, either native (15.25%) or naturalized (16.81%) were more likely to have a managerial position than non-U.S. citizens (9.73%). Native U.S. citizens (3.87%) are more likely to have a post-secondary teaching position outside their field of study than naturalized U.S. citizens (2.69%) and non-U.S. citizens (2.77%).

Next I look at the social and human capital characteristics. Although there are striking differences across doctoral fields of study for working in the same field (ranging from 70.79% for computer and mathematical sciences to about 50% for physical and related sciences and engineering), there are only marginal differences in the rate of being in a managerial position, ranging from 10.73% of those with a degree in computer and mathematical sciences to 14.89% of those with a degree in engineering. Teaching, on the other hand, is less uniformly distributed. Scientists who possess their first doctorate in the Social and Related Sciences are more likely to teach in a non-field specific position (7.12%), whereas scientists who earn their first doctorate in Biology, Agricultural and

Environmental Sciences, Physical and Related Sciences and Engineering Sciences are less likely to teach in a non-field specific position ($p < .0001$).

The field of first bachelor's degree had similar patterns as the doctoral degree field. There was notable variation across working in a doctoral field-specific job over the field of the bachelor's degree, as well as notable variation in working in a known S&E field outside of the degree area, ranging from 16.01% for a bachelor's degree in Social and Related Sciences working in a known S&E field outside the doctoral degree area to 32.73% for S&E related fields. Scientists who earned their bachelor's degree in a Non-S&E Related Field were more likely to be a teacher (15.05%) than those with any other bachelor's field of study, followed by those who earned their undergraduate degree in the Social and Related Sciences and became teachers (4.44%). Again, scientists who earned their undergraduate degree in Biology, Agricultural and Environmental Sciences, Physical and Related Sciences and Engineering were less likely to teach in a non-field specific position ($p < .0001$).

Scientists who worked full time (over 40 hours per week) were more likely to have a managerial position (17.47%) than scientists who worked less than 20 hours per week (8.74%), scientists who worked between 21 and 35 hours (9.87%) and scientists who worked between 36 and 40 hours per week (10.42%). The spread was different for scientists who were teachers. Scientists who worked part time were also more likely to be in a teaching position (4.97%) than scientists who worked less than 20 hours per week (4.70%), scientists who worked between 36 and 40 hours per week (2.70%) and scientists who worked more than 40 hours per week (3.42%).

Lastly, I looked at the control variables. Academic scientists are the most likely to have a job in the field of their doctorate degree compared to those working in the government or business sectors. Of note, scientists who enter the business sector have a much higher likelihood of entering a managerial position (21.64%) than those who work for the government (16.75%) and those who work in academia (7.01%). And only those scientists who work in academia will enter post-secondary teaching positions (7.24%). Unsurprisingly, no scientists who worked for the government or the business sector identified their job as teaching.

Although there is some variation in having a job that matches the field of study by current income, the largest variation is among top earners (\$160,000-\$511,000), of whom 34.76% have a job in field, compared to between about 50-60% for the other income categories. Scientists with a salary of \$100,000-\$160,000 are more likely to be a manager (14.56%) and that percentage is doubled for the highest salary quartile (\$160,000-\$511,000), with 33.32% of scientists in this quartile being managers. This is compared to only 6.18% of scientists in the first salary quartile being managers and 8.39% of scientists in the second salary quartile. The spread of scientists who are post-secondary teachers within the salary percentiles also varies, with 5.35% being in the first salary quartile, 4.33% in the second salary quartile, 2.15% in the third quartile and 1.80% in the fourth and highest quartile.

Table 3: Percentage of Respondents Who Are in Specialty Field Matching, Specialty Field Non-Matching, Managerial or Teaching (Non-Field Specific) Positions

| | | Mismatch (Known Field) | Same Field (Known Field) | Manager (Known Field) | Teacher (Not Field Specific) | F |
|-----------------------------------|--|------------------------------|-----------------------------------|-----------------------------|---------------------------------------|-----------|
| N=63,640 | | | | | | |
| <i>Demographics</i> | | | | | | |
| Gender | | | | | | |
| | Female | 25.84% | 56.42% | 12.83% | 4.91% | |
| | Male | 27.58% | 54.71% | 14.97% | 2.73% | 46.59**** |
| Marital Status | | | | | | |
| | Married | 27.03% | 54.68% | 15.08% | 3.20% | |
| | Not Married | 27.00% | 57.49% | 11.22% | 4.28% | 27.22**** |
| Living with Children | | | | | | |
| | Living with Children | 26.36% | 55.61% | 15.02% | 3.01% | |
| | Not Living with Children | 27.47% | 55.01% | 13.81% | 3.70% | 8.64**** |
| Minority | | | | | | |
| | Yes | 23.17% | 57.71% | 14.57% | 4.54% | |
| | No | 27.42% | 55.01% | 14.27% | 3.31% | 18.08**** |
| Age (Years) | | | | | | |
| | 29 or younger | 29.05% | 64.37% | 5.00% | 1.58% | |
| | 20-34 | 26.17% | 65.66% | 6.11% | 2.06% | |
| | 35-39 | 29.19% | 60.13% | 8.13% | 2.55% | |
| | 40-44 | 27.05% | 57.74% | 12.24% | 2.97% | |
| | 45-49 | 28.56% | 51.29% | 16.25% | 3.89% | |
| | 50-54 | 26.38% | 52.05% | 17.72% | 3.73% | |
| | 55-59 | 25.29% | 52.46 % | 18.22% | 4.02% | |
| | 60-64 | 24.96% | 51.91% | 19.27% | 3.86% | |
| | 65-69 | 27.60% | 51.91% | 16.36% | 4.14% | |
| | 70-75 | 28.23% | 52.66% | 15.14% | 3.97% | 23.23**** |
| Citizenship | | | | | | |
| | US Citizen, Native | 25.89% | 54.99% | 15.25% | 3.87% | |
| | US Citizen, Naturalized | 32.21% | 48.30% | 16.81% | 2.69% | |
| | Non-US Citizen | 26.05% | 61.44% | 9.73% | 2.77% | 50.09**** |
| <i>Social & Human Capital</i> | | | | | | |
| Field of First Doctorate | | | | | | |
| | Computer and Mathematical Sciences | 14.66% | 70.90% | 10.73% | 3.70% | |
| | Biology, Agricultural and Environmental Sciences | 31.22% | 54.50% | 12.51% | 1.77% | |

| | Mismatch (Known Field) | Same Field (Known Field) | Manager (Known Field) | Teacher (Not Field Specific) | F |
|---|---------------------------------------|---|--------------------------------------|---|----------------|
| Physical and Related Sciences | 35.26% | 49.56% | 13.80% | 1.38% | |
| Social and Related Sciences | 16.89% | 61.17% | 14.82% | 7.12% | |
| Engineering | 34.56% | 49.28% | 14.89% | 1.27% | 133.00*** * |
| Field of Bachelor's Degree | | | | | |
| Computer and Mathematical Sciences | 20.47% | 66.95% | 10.05% | 2.53% | |
| Biology, Agricultural and Environmental Sciences | 28.75% | 55.61% | 13.73% | 1.91% | |
| Physical and Related Sciences | 34.79% | 49.75% | 13.68% | 1.78% | |
| Social and Related Sciences | 16.01% | 64.68% | 14.87% | 4.44% | |
| Engineering | 32.74% | 50.62% | 14.95% | 1.69% | |
| S&E Related Fields | 32.73% | 37.97% | 22.32% | 6.99% | |
| Non-S&E Related Fields | 19.27% | 49.75% | 15.93% | 15.05% | |
| Logical Skip | 33.56% | 49.93% | 14.35% | 2.16% | 93.45***** |
| Attended Conferences In the Past Year | | | | | |
| No | 33.46% | 49.77% | 13.81% | 2.96% | |
| Yes | 23.95% | 57.87% | 14.53% | 3.64% | 102.00*** * |
| Number of Professional Memberships | | | | | |
| 0 | 34.93% | 47.06% | 15.51% | 2.50% | |
| 1 | 26.78% | 58.11% | 12.78% | 2.33% | |
| 2 | 25.09% | 56.61% | 14.39% | 3.92% | |
| 3 | 21.54% | 60.09% | 13.68% | 4.68% | |
| 4+ | 22.53% | 57.73% | 15.09% | 4.65% | 41.89***** |
| Hours Per Week Typically Worked | | | | | |
| Less than 20 | 33.35% | 53.20% | 8.74% | 4.70% | |
| 21-35 | 26.25% | 58.91% | 9.87% | 4.97% | |
| 36-40 | 30.30% | 56.59% | 10.42% | 2.70% | |
| 40+ | 24.74% | 54.31% | 17.47% | 3.42% | 46.64***** |
| Controls | | | | | |
| Doctorate Institution Type | | | | | |
| Publicly Controlled | 27.09% | 56.10% | 13.54% | 3.27% | |
| Privately Controlled | 26.93% | 53.34% | 15.97% | 3.76% | |
| Info Not Available, likely Foreign Institution | 15.72% | 76.72% | 4.29% | 3.27% | 9.27***** |
| Bachelor Institution Type | | | | | |
| Publicly Controlled | 25.79% | 54.78% | 15.74% | 3.70% | |
| Privately Controlled | 26.62% | 54.57% | 14.96% | 3.84% | |
| Logical Skip | 33.56% | 49.93% | 14.35% | 2.16% | |

| | Mismatch (Known Field) | Same Field (Known Field) | Manager (Known Field) | Teacher (Not Field Specific) | F | |
|---|---------------------------------------|---|--------------------------------------|---|----------|----------------|
| Info Not Available | | 28.50% | 56.62% | 12.08% | 2.80% | 11.62**** |
| Job Type | | | | | | |
| Academic | | 17.01% | 68.74% | 7.01% | 7.24% | |
| Government | | 31.01% | 52.24% | 16.75% | 0.00% | |
| Business | | 37.00% | 41.36% | 21.64% | 0.00% | 702.78*** * |
| Salary | | | | | | |
| \$0-65,000 | | 26.48% | 62.00% | 6.18% | 5.35% | |
| \$65,000-100,000 | | 22.26% | 65.03% | 8.39% | 4.33% | |
| \$100,000-160,000 | | 29.44% | 53.85% | 14.56% | 2.15% | |
| \$160,000-511,000 | | 30.12% | 34.76% | 33.32% | 1.80% | 310.37*** * |
| Mother's Education | | | | | | |
| Less than HS | | 27.58% | 54.85% | 14.13% | 3.44% | |
| HS Degree | | 26.27% | 54.75% | 15.52% | 3.46% | |
| Some College | | 26.42% | 54.74% | 15.21% | 3.63% | |
| College Degree | | 27.77% | 55.72% | 13.41% | 3.10% | |
| Master's | | 27.00% | 56.29% | 13.08% | 3.63% | |
| Professional Degree | | 29.93% | 53.51% | 13.01% | 3.56% | |
| Doctorate | | 26.51% | 56.86% | 13.18% | 3.45% | |
| Not Applicable (e.g. single parent household) | | 22.26% | 66.35% | 10.74% | 0.64% | 1.90** |

+p<.10, *p<.05, **p<.01, ***p<.001, ****p<.0001

Multivariate Results: Specialty Field of Study Match, Overall

I estimate a series of logistic regression models predicting the probability of whether someone is in the same field as their principal field of study and specialty field of study. With the exception of gender, whether I categorize the dependent variable as a principal job/field match or a specialty job/field match, I see similar directional associations with similar magnitudes. Because of the similarities between tables, I combine them in Table 3. Table 3 shows results for specialty field matches for all study

variables. Models 1-3 show results for demographics, human and social capital, and controls. Model 3 shows full model results for all study variables.

Demographics

Model 1 shows the odds ratios and 95% confidence intervals for the demographic predictor variables examining the probability of whether a PhD level scientist holds a job in their same field as their broad or specialty field for their doctoral degree or not. When we look at the outcome of a job being in the same broad field as the PhD, there is no discernible difference between men and women. However, there are gender differences in job specialization within specialty field, consistent with my first hypothesis. The odds of having a job that matches the specialty field of study increases slightly for women (5%) as compared to men, holding all demographic variables constant (OR=1.056, $p < .05$). However, this gender discrepancy reverses and grows slightly in magnitude as additional variables are added to the models.

Married scientists and those with children are not statistically different from those who are not married or who do not have children in the odds of having a job in their field of study. Model 1 shows that race and ethnicity to have a significant association with having a job in a specialty field of study. The odds of minorities having a job match are 10.6% higher than non-minorities (OR=1.106, $p < .001$), but this association is explained by human and social capital variables. Age is statistically associated with staying in the same field ($F(19.62, p < .0001)$). As in the bivariate associations, older scientists are about 35% less likely to be in the same field than younger scientists. As in the bivariate analyses, being a US citizen is also statistically associated with being in the same field ($F(53.97, p < .0001)$). Compared to native-born U.S. citizens, the odds of finding a job

match in the specialty field of study decrease by 22% for naturalized US citizens (OR=.788, $p<.0001$) and increases by 21% for non-US citizens (OR=1.207, $p<.0001$).

Human & Social Capital

Model 2 adds in proxy measures of human and social capital. The fields in which the respondents received their first doctorate were statistically significantly associated with having an in-degree job ($F(39.97, p<.0001)$). Scientists with a PhD in Social and Related Sciences were more likely to have a job in-field than any other degree area. Even after accounting for PhD degree, the field of a respondent's first bachelor degree was also statistically significant ($F(22.94, p<.0001)$). Of the bachelor-level fields, the odds of finding a job match in the same field of study of the PhD decreased 17% for those who majored in Non S&E Related Fields in college ($p<.05$) as compared to those who majored in Computer and Mathematical Sciences. If a respondent majored in Social and Related Sciences at the bachelor's level, the odds of doctorate and field match increased by 46% (OR=1.464, ($p<.0001$)) as compared to majoring in Computer and Mathematical Sciences in college.

In this model, the proxies for tangible and intangible human capital are significantly associated with the outcome variable. Respondents who attended one or more professional conferences within the past year had 17% higher odds of having a degree/field match than their colleagues who did not attend conferences ($F(26.79, p<.0001)$). Similarly, respondents who possessed memberships in even just one professional association had a significantly higher likelihood of having a job/field match than those were not part of professional associations ($F(45.48, p<.0001)$). The odds of having a job/degree match decreases by 10% for respondents who works full time as

compared to half (OR=.895, $p<.05$), although this association is modest and explained by the control variables.

Controls

The control variables added provided additional context to Model 3. There is no difference in having a job that matches one's field for those who receive their bachelor's or doctorate degree from a public or private institution, although those whose doctorate institution type was not available (possibly because of being from a foreign institution) were much more likely to have a job that matched their field.

The type of job a respondent currently holds (i.e. academic, government or business) was significantly associated with a job/field match ($F(513.74, p<.0001)$). Holding a government job decreased the odds of a scientist having a job/degree field match by 48% (OR=.525, $p<.0001$) relative to being in an academic job. Holding a job in the business sector further decreased the odds of a respondent finding a job/education match – a decrease in odds of 62% relative to being in an academic job (OR=.382, $p<.0001$). Salary also had a significant association ($F(126.65, p<.0001)$). Those in the 2nd quartile (\$65,000-\$100,000 category) had a 15% increase in the odds of having a job/field match than those in the 1st quartile category (\$0-\$65,000) (OR=1.154, $p<.0001$). As salaries increased, the odds of finding a job/field match decreased. Those in the 4th quartile (\$160,000-\$511,000) had a 50% odds decrease in a job/field match (OR=.496, $p<.0001$). The education of the respondent's mother was not associated with holding a job that matched one's degree field ($F(1.22, p=.29)$).

Table 4: Odds Ratios and 95% Confidence Intervals from Logistic Regression Models Predicting Education/Job Broad Matches by Demographics, Human Capital and Social Capital Characteristics

| | | Model 1 | | Model 2 | | Model 3 | |
|----------------------|--------------------------|------------|-------------|------------|-------------|----------------|-------------|
| | | Odds Ratio | 95% CI | Odds Ratio | 95% CI | Odds Ratio | 95% CI |
| <i>Demographics</i> | | | | | | | |
| Gender | | | | | | | |
| | Male | | | | | | |
| | Female | 1.010 | (0.96-1.06) | 0.945* | (0.90-1.00) | 0.880s*** * | (0.83-0.93) |
| Marital Status | | | | | | | |
| | Not Married | | | | | | |
| | Married | 0.948 | (0.89-1.01) | 0.953 | (0.89-1.01) | 0.982 | (0.92-1.05) |
| Living with Children | | | | | | | |
| | Not Living with Children | | | | | | |
| | Living with Children | 1.007 | (0.95-1.06) | 1.018 | (0.96-1.08) | 1.009 | (0.95-1.07) |
| Minority | | | | | | | |
| | No | | | | | | |
| | Yes | 1.057* | (0.99-1.12) | 1.018 | (0.95-1.09) | 0.943 | (0.88-1.01) |
| Age (Years) | | | | | | | |
| | 29 or younger | | | | | | |
| | 30-34 | 0.995 | (0.79-1.25) | 0.958 | (0.75-1.22) | 0.917 | (0.72-1.17) |
| | 35-39 | 0.815 | (0.65-1.02) | 0.752 | (0.59-0.95) | 0.765* | (0.60-0.97) |
| | 40-44 | 0.774* | (0.62-0.97) | 0.684** | (0.54-0.87) | 0.711** | (0.56-0.91) |
| | 45-49 | 0.616***** | (0.49-0.78) | 0.542***** | (0.43-0.69) | 0.591***** | (0.46-0.76) |
| | 50-54 | 0.650***** | (0.52-0.82) | 0.587***** | (0.46-0.75) | 0.638***** | (0.50-0.82) |
| | 55-59 | 0.666***** | (0.53-0.84) | 0.580***** | (0.46-0.74) | 0.626***** | (0.49-0.80) |
| | 60-64 | 0.621***** | (0.49-0.78) | 0.529***** | (0.42-0.67) | 0.590***** | (0.46-0.76) |
| | 65-69 | 0.614***** | (0.49-0.78) | 0.527***** | (0.41-0.68) | 0.591***** | (0.46-0.76) |
| | 70-75 | 0.626*** | (0.49-0.80) | 0.545***** | (0.42-0.71) | 0.615***** | (0.47-0.80) |
| Citizenship | | | | | | | |
| | US Citizen, Native | | | | | | |

| | | | | | | | |
|--|---|------------|-----------------|------------|-----------------|-----------|-----------------|
| | US Citizen, Naturalized | 0.847***** | (0.79- 0.91) | 0.894** | (0.83- 0.96) | 0.861** | (0.78- 0.96) |
| | Non-US Citizen | 1.274***** | (1.20- 1.35) | 1.269***** | (1.19- 1.36) | 0.970 | (0.86- 1.09) |
| <i>Social & Human Capital</i> | | | | | | | |
| Field of First Doctorate | | | | | | | |
| | Computer and Mathematical Sciences | | | | | | |
| | Biology, Agricultural and Environmental Sciences | | | 0.412**** | (0.35- 0.48) | 0.404**** | (0.34- 0.48) |
| | Physical and Related Sciences | | | 0.398**** | (0.34- 0.47) | 0.384**** | (0.33- 0.45) |
| | Social and Related Sciences | | | 0.478**** | (0.41- 0.56) | 0.451**** | (0.38- 0.53) |
| | Engineering | | | 0.501**** | (0.43- 0.59) | 0.547**** | (0.46- 0.64) |
| Field of Bachelor's Degree | | | | | | | |
| | Computer and Mathematical Sciences | | | | | | |
| | Biology, Agricultural and Environmental Sciences | | | 1.154 | (0.99- 1.35) | 1.095 | (0.93- 1.28) |
| | Physical and Related Sciences | | | 0.909 | (0.78- 1.06) | 0.929 | (0.79- 1.09) |
| | Social and Related Sciences | | | 1.443**** | (1.23- 1.69) | 1.420**** | (1.20- 1.68) |
| | Engineering | | | 0.911 | (0.78- 1.06) | 0.945 | (0.81- 1.11) |
| | S&E Related Fields | | | 0.626**** | (0.51- 0.77) | 0.618**** | (0.50- 0.77) |
| | Non-S&E Related Fields | | | 0.790** | (0.67- 0.93) | 0.707**** | (0.59- 0.84) |
| | Logical Skip (e.g. respondent skipped undergrad) | | | 0.890 | (0.70- 1.13) | 1.009 | (0.78- 1.31) |
| Attended Conferences In the Past Year | | | | | | | |
| | No | | | | | | |
| | Yes | | | 1.164**** | (1.09- 1.24) | 1.102** | (1.03- 1.17) |
| Number of Professional Memberships | | | | | | | |

| | | | | | |
|--|--|-----------|-------------|-------------|-------------|
| | 0 | | | | |
| | 1 | 1.542**** | (1.41-1.64) | 1.424**** | (1.32-1.54) |
| | 2 | 1.416**** | (1.31-1.53) | 1.237**** | (1.14-1.34) |
| | 3 | 1.537**** | (1.41-1.68) | 1.281**** | (1.17-1.40) |
| | 4+ | 1.442**** | (1.32-1.58) | 1.203**** | (1.10-1.32) |
| Hours Per Week Typically Worked | | | | | |
| | Less than 20 | | | | |
| | 21-35 | 1.114 | (0.97-1.28) | 1.146 | (0.99-1.32) |
| | 36-40 | 1.062 | (0.95-1.19) | 1.076 | (0.95-1.22) |
| | 40+ | 0.856** | (0.77-0.96) | 0.914 | (0.81-1.03) |
| <i>Controls</i> | | | | | |
| Doctorate Institution Type | | | | | |
| | Publicly Controlled | | | | |
| | Privately Controlled | | | 0.918** | (0.87-0.97) |
| | Info Not Available, likely Foreign Institution | | | 2.225* | (1.04-4.78) |
| Bachelor Institution Type | | | | | |
| | Publicly Controlled | | | | |
| | Privately Controlled | | | 0.992 | (0.93-1.06) |
| | Logical Skip (e.g. respondent skipped undergrad) | | | 1 (Omitted) | |
| | Info Not Available | | | 1.164** | (1.04-1.30) |
| Job Type | | | | | |
| | Academic | | | | |
| | Government | | | 0.735**** | (0.67-0.81) |
| | Business | | | 0.469**** | (0.44-0.50) |
| Salary | | | | | |
| | \$0-65,000 | | | | |
| | \$65,000-100,000 | | | 1.194**** | (1.11-1.28) |
| | \$100,000-160,000 | | | 0.996 | (0.92-1.07) |

| | | | | | |
|--|--|---------------|-----------------|---------------|-----------------|
| | \$160,000- 511,000 | | | 0.484**** | (0.44- 0.53) |
| Mother's Education | Less than HS | | | | |
| | HS Degree | | | 1.039 | (0.95- 1.14) |
| | Some College | | | 0.993 | (0.89- 1.08) |
| | College Degree | | | 1.02 | (0.92- 1.11) |
| | Master's | | | 0.981 | (0.89- 1.09) |
| | Professional Degree | | | 0.891 | (0.76- 1.04) |
| | Doctorate | | | 0.977 | (0.82- 1.16) |
| | Not Applicable (e.g. single parent household) | | | 1.406 | (0.75- 2.63) |
| <i>Intercept</i> | | 2.224**** | (1.73- 2.86) | 3.792**** | (2.82- 5.11) |
| Model Fit Statistics | | | | | |
| N | | 63,63 5 | | 60,730 | 60,730 |
| F-test | | 24.71 **** | | 36.36* *** | 49.67** ** |
| DF | | 63,63 4 | | 60,729 | 63,729 |
| +p<.10, *p<.05, **p<.01, ***p<.001, ****p<.0001 | | | | | |

Table 5: Odds Ratios and 95% Confidence Intervals from Logistic Regression Models Predicting Education/Job Specialty Matches by Demographics, Human Capital and Social Capital Characteristics

| | | Model 1 | | Model 2 | | Model 3 | |
|----------------------|--------------------------|---------------|-------------|------------|-------------|------------|-------------|
| | | Odds Ratio | 95% CI | Odds Ratio | 95% CI | Odds Ratio | 95% CI |
| <i>Demographics</i> | | | | | | | |
| Gender | | | | | | | |
| | Male | | | | | | |
| | Female | 1.056* | (1.01-1.11) | 0.961 | (0.91-1.01) | 0.897**** | (0.85-0.95) |
| Marital Status | | | | | | | |
| | Not Married | | | | | | |
| | Married | 0.950 | (0.89-1.01) | 0.959 | (0.90-1.02) | 0.990 | (0.93-1.06) |
| Living with Children | | | | | | | |
| | Not Living with Children | | | | | | |
| | Living with Children | 1.029 | (0.97-1.09) | 1.035 | (0.98-1.09) | 1.023 | (0.97-1.08) |
| Minority | | | | | | | |
| | No | | | | | | |
| | Yes | 1.106*** | (1.04-1.18) | 1.045 | (0.98-1.11) | 0.963 | (0.90-1.03) |
| Age (Years) | | | | | | | |
| | 29 or younger | | | | | | |
| | 30-34 | 1.060 | (0.84-1.33) | 1.032 | (0.82-1.30) | 0.980 | (0.77-1.24) |
| | 35-39 | 0.842 | (0.67-1.06) | 0.781* | (0.62-0.98) | 0.787* | (0.62-0.99) |
| | 40-44 | 0.797 | (0.63-1.00) | 0.721** | (0.57-0.91) | 0.738* | (0.58-0.93) |
| | 45-49 | 0.637*** * | (0.51-0.80) | 0.570**** | (0.45-0.72) | 0.610**** | (0.48-0.77) |
| | 50-54 | 0.671** | (0.53-0.84) | 0.609**** | (0.48-0.77) | 0.650**** | (0.51-0.82) |
| | 55-59 | 0.678** | (0.54-0.85) | 0.605**** | (0.48-0.76) | 0.640**** | (0.50-0.81) |
| | 60-64 | 0.677** | (0.54-0.85) | 0.569**** | (0.45-0.72) | 0.624**** | (0.49-0.79) |
| | 65-69 | 0.665** | (0.53-0.84) | 0.564**** | (0.44-0.72) | 0.620**** | (0.48-0.80) |
| | 70-75 | 0.684** | (0.53-0.88) | 0.588**** | (0.46-0.76) | 0.650** | (0.50-0.84) |
| Citizenship | | | | | | | |
| | US Citizen, Native | | | | | | |

| | | | | | | | |
|--|---|---------------|-----------------|------------|-----------------|------------|-----------------|
| | US Citizen, Naturalized | 0.788*** * | (0.74- 0.84) | 0.889** | (0.83- 0.96) | 0.885** | (0.80- 0.98) |
| | Non-US Citizen | 1.207*** * | (1.14- 1.28) | 1.274***** | (1.19- 1.36) | 0.995 | (0.89- 1.12) |
| <i>Social & Human Capital</i> | | | | | | | |
| Field of First Doctorate | | | | | | | |
| | Computer and Mathematical Sciences | | | | | | |
| | Biology, Agricultural and Environmental Sciences | | | 0.452***** | (0.39- 0.52) | 0.447***** | (0.38- 0.52) |
| | Physical and Related Sciences | | | 0.421***** | (0.36- 0.49) | 0.413***** | (0.35- 0.48) |
| | Social and Related Sciences | | | 0.519***** | (0.45- 0.60) | 0.494***** | (0.42- 0.58) |
| | Engineering | | | 0.421***** | (0.36- 0.49) | 0.467***** | (0.40- 0.54) |
| Field of Bachelor's Degree | | | | | | | |
| | Computer and Mathematical Sciences | | | | | | |
| | Biology, Agricultural and Environmental Sciences | | | 1.117 | (0.96- 1.29) | 1.081 | (0.93- 1.26) |
| | Physical and Related Sciences | | | 0.939 | (0.81- 1.09) | 0.983 | (0.84- 1.15) |
| | Social and Related Sciences | | | 1.464***** | (1.26- 1.71) | 1.471***** | (1.25- 1.73) |
| | Engineering | | | 0.885 | (0.77- 1.02) | 0.940 | (0.81- 1.09) |
| | S&E Related Fields | | | 0.684***** | (0.56- 0.84) | 0.695** | (0.56- 0.87) |
| | Non-S&E Related Fields | | | 0.826* | (0.70- 0.97) | 0.739***** | (0.62- 0.88) |
| | Logical Skip | | | 0.819 | (0.65- 1.04) | 0.908 | (0.70- 1.17) |
| Attended Conferences In the Past Year | | | | | | | |
| | No | | | | | | |
| | Yes | | | 1.174***** | (1.10- 1.25) | 1.090** | (1.02- 1.16) |
| Number of Professional Memberships | | | | | | | |
| | 0 | | | | | | |
| | 1 | | | 1.547***** | (1.44- 1.67) | 1.426***** | (1.32- 1.54) |

| | | | | | |
|---------------------------------|--|-----------|-------------|----------------|-------------|
| | 2 | 1.451**** | (1.34-1.57) | 1.223**** | (1.13-1.33) |
| | 3 | 1.644**** | (1.51-1.79) | 1.305**** | (1.19-1.43) |
| | 4+ | 1.557**** | (1.42-1.70) | 1.220**** | (1.11-1.34) |
| Hours Per Week Typically Worked | | | | | |
| | Less than 20 | | | | |
| | 21-35 | 1.109 | (0.97-1.27) | 1.145 | (0.99-1.32) |
| | 36-40 | 0.996 | (0.89-1.11) | 1.045 | (0.93-1.18) |
| | 40+ | 0.895* | (0.80-1.00) | 0.947 | (0.84-1.07) |
| <i>Controls</i> | | | | | |
| Doctorate Institution Type | | | | | |
| | Publicly Controlled | | | | |
| | Privately Controlled | | | 0.963 | (0.91-1.02) |
| | Info Not Available, likely Foreign Institution | | | 2.713* | (1.27-5.79) |
| Bachelor Institution Type | | | | | |
| | Publicly Controlled | | | | |
| | Privately Controlled | | | 1.002 | (0.94-1.07) |
| | Logical Skip (e.g. respondent skipped undergrad) | | | 1 (Omitted) | |
| | Info Not Available | | | 1.109 | (0.99-1.24) |
| Job Type | | | | | |
| | Academic | | | | |
| | Government | | | 0.525**** | (0.48-0.57) |
| | Business | | | 0.382**** | (0.36-0.41) |
| Salary | | | | | |
| | \$0-65,000 | | | | |
| | \$65,000-100,000 | | | 1.154**** | (1.08-1.24) |
| | \$100,000-160,000 | | | 0.977 | (0.91-1.05) |
| | \$160,000-511,000 | | | 0.496**** | (0.45-0.55) |
| Mother's Education | | | | | |
| | Less than HS | | | | |

| | | | | | |
|--|---|---------------|-------------|---------------|---------------|
| | HS Degree | | | 1.020 | (0.93-1.11) |
| | Some College | | | 0.994 | (0.90-1.09) |
| | College Degree | | | 1.009 | (0.92-1.10) |
| | Master's | | | 0.965 | (0.87-1.07) |
| | Professional Degree | | | 0.842* | (0.72-0.99) |
| | Doctorate | | | 1.023 | (0.86-1.21) |
| | Not Applicable (e.g. single parent household) | | | 1.284 | (0.76-2.17) |
| <i>Intercept</i> | | 1.589*** * | (1.24-2.04) | 6.22**** | (1.87-3.34) |
| Model Fit Statistics | | | | | |
| N | | 60,623 | | 60,605 | |
| F-test | | 25.60* *** | | 39.81 **** | 58.50** ** |
| DF | | 63,622 | | 60,604 | |
| +p<.10, *p<.05, **p<.01, ***p<.001, ****p<.0001 | | | | | |

Multinomial Results: Specialty Field of Study Match and Job Specialization

I expanded my analysis of specialty field and I estimate a series of multinomial regression models predicting the probability of whether someone is in (1) a known job-field mismatch, (2) a managerial or (3) teaching position where the field is unknown versus (4) a job that matches their specialty field of study. Table 4 shows the multinomial regression results examining mismatches of specialty field and job specialization.

Demographics

Gender is a strong predictor of job specialization. The relative risk ratio of going into the teaching field rather than finding a credential match is 33.3% higher for women scientists than for men scientists (RRR=1.333, $p<.0001$). Interestingly, the relative risk ratio of entering a managerial field rather than finding a credential match is 12.1% higher for women scientists than for men scientists (RRR=1.121 $p<.05$) and of having a more general S&E field mismatch is 9.3% higher for women scientists than for men scientists. Marital status, on the other hand, only matters for predicting non-field specific managerial roles. The relative risk of entering a managerial position versus finding a credential match is 16.6% times greater for scientists who are married compared to scientists who are not married (RRR=1.166, $p<.01$). Scientists who live with children as compared to those who do not have a 13.1% increase in relative risk of being a manager as opposed to finding a credential match (RRR=1.131, $p<.01$). The opposite is true for teaching and more general field-job mismatch positions. Scientists who live with children as compared to those who do not have a 13% decrease in the relative risk of being a teacher and a 7% lower risk of a more general mismatch versus having a credential match. The relative risk of being a manager rather than finding a job with a credential

match is 24.2% more likely for minorities than non-minorities (RRR=1.242, $p<.0001$). I found that age only matters for managerial positions. Scientists in their 40s, 50s, 60s and 70s compared to scientists 29 years of age or younger have a two to three times higher relative risk of being in a managerial position as compared to being in a credential match. The relative risk of being in a teaching position rather than a job with a credential match is 26% lower for non-U.S. citizens than native U.S. citizens (RRR=0.737, $p<.05$). Having a more general S&E job that does not match the field of study is 1.147 times greater for naturalized U.S. citizens than native-born U.S. citizens (RRR=1.147, $p<.05$).

Human & Social Capital

Overwhelmingly, scientists with a PhD in Physical and Related Sciences and those with degrees in Social and Related Sciences were statistically far more likely to work as managers or experience a more general job-field of study mismatch compared to scientists with a PhD in Computer and Mathematical Sciences ($p<.0001$). Two of those same fields – Physical and Related Sciences and Engineering – were related to a statistically significant relative decrease (compared to scientists with a PhD in Computer and Mathematical Sciences) also experience relative decrease in the risk of becoming a post-secondary teacher as opposed to finding a credential match ($p<.0001$). Scientists with a PhD in the field of Biology, Agricultural and Environmental Sciences (compared to scientists with a PhD in Computer and Mathematical Sciences) is also related to a relative decrease in the risk of becoming a post-secondary teacher as opposed to finding a credential match ($p<.0001$). Interestingly, compared to scientists with a PhD in Computer and Mathematical Science, scientists who earned a PhD in the Social and Related Sciences had a relative risk of being a teacher rather than finding a credential

match that was 63.4% higher than those who earned a PhD in the Computer and Mathematical Sciences.

Not surprisingly, the scientists' field of bachelor's degree did not have as strong an impact on job outcomes as their PhD. Compared to scientists with a bachelor's in Computer and Mathematical Sciences, STEM PhDs with a bachelor's in Biology, Agricultural and Environmental Sciences, S&E Related Fields and Non-S&E Related Fields had a higher risk of entering a non-field specific managerial position and generally a lower risk of a non-field specific job-credential mismatch. STEM PhDs with a bachelor's degree in the Physical and Related Sciences, Engineering, S&E Related Fields, and Non-S&E Related fields compared to scientists with a bachelor's degree in Computer and Mathematical Sciences have a two to three times higher relative risk of being in a teaching position as compared to being in a job with a credential match.

The relative risk of entering a managerial position versus holding a job with a credential match is 15.2% greater for scientists who have attended conferences in the past year compared to scientists who hadn't (RRR=1.152, $p<.01$). The relative risk of having a teaching position or a more general job-credential mismatch versus finding a credential match is 31% less and 14% less, respectively, for scientists who have attended conferences in the past year compared to scientists who hadn't (RRR=0.696, $p<.0001$ and RRR=0.862, $p<.0001$). The number of professional memberships a scientist holds (as compared to scientists who do not have any professional memberships) are associated with about a 20% decrease in the risk of having a managerial job or having a more general credential-job mismatch as compared to having a credential-job match. Similarly, having one professional memberships, (as compared to scientists who are not part of

professional memberships) are associated with a 33% decrease relative probability in having a teaching position as compared to finding a credential match (RRR=0.665, $p<.01$).

Controls

Type of doctorate institution had a significant relationship with going into a teaching position. The relative risk of holding a teaching position rather than having a job with a credential match is 24.7% higher for scientists who attend a privately controlled doctoral institution rather than a publicly controlled doctoral institution (RRR=1.247, $p<.01$). The type of collegiate institution had no significant association in predicting whether a scientist would go into a managerial or teaching position. Job type was a significant predictor of going into a teaching or managerial position. I found scientists who find a job in government or business (compared to scientists who enter academia) have a three or four times higher relative risk of being in a managerial position as compared to those who have a credential-job match. On the other hand, scientists who find a job in government or business (as compared to scientists who enter academia) are significantly less likely to have a teaching position as compared to hold a credential match. Mother's education was not a strong predictor of holding a managerial or teaching position.

Table 6: Relative Risk Ratios and 95% Confidence Intervals Predicting a Mismatch of a Specialty Field of Study, Job in a Managerial Position (Field not specified) and Teacher (Field not specified by Demographics, Human and Social Capital Proxies, and Controls)

| | Match in Specialty Field (Base) | Mismatch in Specialty Field Relative Risk Ratio | 95% CI | Manager, Field Unknown Relative Risk Ratio | 95% CI | Teacher, Field Unknown Relative Risk Ratio | 95% CI |
|----------------------|--|--|-------------|---|-------------|---|-------------|
| <i>Demographics</i> | | | | | | | |
| Gender | | | | | | | |
| | Female | 1.093** | (1.03-1.16) | 1.121* | (1.03-1.22) | 1.333*** * | (1.16-1.53) |
| Marital Status | | | | | | | |
| | Married | 0.969 | (0.90-1.04) | 1.166** | (1.05-1.29) | 0.919 | (0.79-1.07) |
| Living with Children | | | | | | | |
| | Living with Children | 0.929* | (0.87-0.99) | 1.131** | (1.04-1.24) | 0.868 | (0.75-1.00) |
| Minority | | | | | | | |
| | Yes | 0.940 | (0.87-1.01) | 1.242*** * | *1.12-1.38) | 1.069 | (0.91-1.25) |
| Age (Years) | | | | | | | |
| | 29 or younger | | | | | | |
| | 30-34 | 1.007 | (0.78-1.30) | 1.228 | (0.75-2.01) | 1.015 | (0.40-2.59) |
| | 35-39 | 1.268 | (0.98-1.63) | 1.564 | (0.96-2.55) | 1.287 | (0.51-3.23) |
| | 40-44 | 1.247 | (0.96-1.61) | 2.147** | (1.32-3.50) | 1.491 | (0.59-3.74) |
| | 45-49 | 1.424** | (1.10-1.84) | 2.863*** | (1.75-4.67) | 2.046 | (0.81-5.16) |
| | 50-54 | 1.257 | (0.97-1.63) | 2.951*** * | (1.81-4.80) | 2.161 | (0.85-5.47) |
| | 55-59 | 1.259 | (0.97-1.63) | 3.133*** * | (1.92-5.11) | 2.026 | (0.80-5.13) |
| | 60-64 | 1.301 | (1.00-1.69) | 3.448*** * | (2.11-5.64) | 1.667 | (0.66-4.22) |
| | 65-69 | 1.395* | 1.06-1.29) | 3.220*** * | (1.95-5.32) | 1.692 | (0.66-4.35) |
| | 70-75 | 1.267 | (0.95-1.69) | 3.402*** * | (2.03-5.71) | 1.600 | (0.61-4.18) |
| Citizenship | | | | | | | |
| | US Citizen, Native | | | | | | |
| | US Citizen, | 1.147* | (1.02-1.29) | 1.107 | (0.94-1.30) | 1.062 | (0.82-1.37) |

| | | | | | | |
|---|-----------|-----------------|---------------|-----------------|---------------|-----------------|
| Naturalized Non-US Citizen | 0.975 | (0.85- 1.12) | 1.171 | (0.97- 1.41) | 0.737* | (0.55- 0.99) |
| <i>Social & Human Capital</i> | | | | | | |
| Field of First Doctorate | | | | | | |
| Computer and Mathematical Sciences | | | | | | |
| Biology, Agricultural and Environmental Sciences | 3.936**** | (3.25- 4.77) | 1.205 | (0.95- 1.53) | 0.424*** * | (0.28- 0.64) |
| Physical and Related Sciences | 4.026**** | (3.32- 4.89) | 1.585*** * | (1.25- 2.01) | 0.302*** * | (0.20- 0.46) |
| Social and Related Sciences | 2.177**** | (1.77- 2.68) | 1.544*** * | (1.22- 1.96) | 1.645** | (1.19- 2.29) |
| Engineering | 3.462**** | (2.85- 4.20) | 1.377** | (1.10- 1.73) | 0.390*** * | (0.27- 0.57) |
| Field of Bachelor's Degree | | | | | | |
| Computer and Mathematical Sciences | | | | | | |
| Biology, Agricultural and Environmental Sciences | 0.670**** | (0.56- 0.80) | 1.452** | (1.14- 1.85) | 1.557 | (0.98- 2.47) |
| Physical and Related Sciences | 0.795* | (0.67- 0.95) | 1.159 | (0.91- 1.47) | 2.757*** * | (1.72- 4.42) |
| Social and Related Sciences | 0.511**** | (0.42- 0.62) | 1.146 | (0.90- 1.47) | 1.006 | (0.67- 1.50) |
| Engineering | 0.818* | (0.68- 0.98) | 1.298* | (1.03- 1.64) | 2.660*** * | (1.77- 4.01) |
| S&E Related Fields | 1.228 | (0.95- 1.58) | 1.401 | (0.98- 2.00) | 2.566*** * | (1.54- 4.27) |
| Non-S&E Related Fields | 0.770* | (0.63- 0.95) | 1.624*** * | (1.25- 2.11) | 4.549*** * | (3.10- 6.68) |
| Logical Skip (e.g. respondent skipped undergraduate) | 0.981 | (0.73- 1.32) | 1.120 | (0.75- 1.67) | 1.450 | (0.78- 2.69) |
| Attended Conferences In the Past Year | | | | | | |
| Yes | 0.862**** | (0.80- 0.93) | 1.152** | (1.04- 1.27) | 0.696*** * | (0.58- 0.83) |
| Number of Professional Memberships | | | | | | |
| 0 | | | | | | |
| 1 | 0.717**** | (0.66- 0.78) | 0.678*** * | (0.60- 0.77) | 0.665** | (0.52- 0.84) |
| 2 | 0.821**** | (0.75- 0.90) | 0.809** | (0.71- 0.92) | 0.913 | (0.73- 1.15) |
| 3 | 0.744**** | (0.67- 0.81) | 0.788** | (0.69- 0.88) | 0.900 | (0.70- 0.99) |

| | | | | | | | |
|---------------------------------|--|----------|-------------|---------------|-------------|---------------|---------------------|
| | | | 0.83) | | 0.91) | | 1.15) |
| | 4+ | 0.850** | (0.76-0.95) | 0.824** | (0.71-0.95) | 0.780 | (0.61-1.00) |
| Hours Per Week Typically Worked | | | | | | | |
| | Less than 20 | | | | | | |
| | 21-35 | 0.847* | (0.73-0.99) | 0.939 | (0.72-1.22) | 1.021 | (0.73-1.43) |
| | 36-40 | 0.907 | (0.79-1.04) | 1.080 | (0.86-1.36) | 0.879 | (0.65-1.19) |
| | 40+ | 0.849* | (0.74-0.97) | 1.824*** * | (1.46-2.27) | 0.890 | (0.66-1.19) |
| <i>Controls</i> | | | | | | | |
| Doctorate Institution Type | | | | | | | |
| | Publicly Controlled | | | | | | |
| | Privately Controlled | 1.006 | (0.94-1.07) | 1.078 | (0.99-1.18) | 1.247** | (1.08-1.43) |
| | Info Not Available, likely Foreign Institution | 0.365* | (0.16-0.85) | 0.424 | (0.84-2.14) | 0.253 | (0.03-2.13) |
| Bachelor Institution Type | | | | | | | |
| | Publicly Controlled | | | | | | |
| | Privately Controlled | 1.036 | (0.96-1.11) | 0.935 | (0.85-1.03) | 0.967 | (0.82-1.14) |
| | Info Not Available | 0.948 | (0.84-1.07) | 0.795** | (0.67-0.94) | 0.937 | (0.72-1.23) |
| Job Type | | | | | | | |
| | Academic | | | | | | |
| | Government | 2.187*** | (1.98-2.42) | 3.291*** * | (2.86-3.78) | 1.55e-10*** | (1.36e-10-1.77e-10) |
| | Business | 3.028*** | (2.83-3.24) | 4.504*** * | (4.07-4.98) | 1.56e-10*** | (1.41e-10-1.73e-10) |
| Salary | | | | | | | |
| | \$0-65,000 | | | | | | |
| | \$65,000-100,000 | 0.835*** | (0.77-0.91) | 1.157* | (1.01-1.33) | 0.690*** * | (0.58-0.82) |
| | \$100,000-160,000 | 0.928 | (0.85-1.01) | 1.609*** * | (1.40-1.85) | 0.677*** * | (0.55-0.83) |
| | \$160,000-511,000 | 1.373*** | (1.23-1.53) | 4.589*** * | (3.95-5.33) | 1.126 | (0.86-1.47) |
| Mother's Education | | | | | | | |
| | Less than HS | | | | | | |
| | HS Degree | 0.964 | (0.87-1.07) | 1.022 | (0.89-1.17) | 0.967 | (0.77-1.21) |
| | Some College | 0.987 | (0.88-1.10) | 1.025 | (0.88-1.19) | 1.040 | (0.81-1.34) |
| | College Degree | 1.007 | (0.91-1.12) | 0.963 | (0.84-1.11) | 0.944 | (0.74-1.20) |

| | | | | | | |
|---|-----------|-------------|---------------|-------------|---------------|-------------|
| Master's | 1.053 | (0.94-1.18) | 0.980 | (0.83-1.15) | 1.108 | (0.85-1.44) |
| Professional Degree | 1.235* | (1.03-1.48) | 1.128 | (0.88-1.44) | 1.025 | (0.67-1.56) |
| Doctorate | 1.018 | (0.84-1.23) | 0.901 | (0.69-1.18) | 0.985 | (0.69-1.42) |
| Not Applicable (e.g. single parent household) | 0.813 | (0.42-1.58) | 0.914 | (0.44-1.90) | 0.217 | (0.04-0.89) |
| <i>Intercept</i> | 0.180**** | (0.13-0.26) | 0.005*** * | (0.00-0.01) | 0.097*** * | (0.03-0.27) |

Model Fit Statistics

| | |
|--|-------------|
| N | 60,610 |
| F-test | 3110.07**** |
| DF | 60,609 |
| +p<.10, *p<.05, **p<.01, ***p<.001, ****p<.0001 | |

SUMMARY

Discussion

The summary table above focuses only on the main indicators. Because I did not have specific hypotheses over the control variables, I did not include them in the summary table. Perhaps the most surprising finding is that approximately 40-45% of respondents find a job outside of their broad doctorate field of study. After 5 to 10 years of investment in time, money and personal sacrifice, this finding is consequential. Below I summarize which type of scientists are more likely to switch their fields of doctoral study and account for this large majority.

Note that my conceptual model presented above posits that the accumulations of certain experiences, such as going to conferences or being a part of professional memberships, is directionally associated with finding a job credential match. This causal model may in fact run the other direction. Scientists who are in fields who match their field of PhD are perhaps more likely to select into a professional membership, attend

conferences or seek certain positions. The associations I find within this thesis should be considered as a two-way correlation and not merely a one-way causal model.

Although women were significantly less likely to secure a job-credential match than men, confirming my first hypothesis, the bivariate results and the multinomial results show unique differences across men and women scientists. Women scientists with PhDs were more likely to not be married, were more likely to be a minority and more likely to be native U.S. citizens than men scientists. There were significant differences in the fields that men and women entered, both at the doctoral level and the bachelor's level. We may expect women who are in certain fields to be more likely to leave because of the "chilly climate" they may encounter in certain STEM due to their gender identity (Britton 2017), but future research should explore the specific correlates that may differ for men and women and to establish a baseline. Women scientists were more likely than men scientists to attend a conference in the past year, and more likely to work part-time than full-time. Women scientists were significantly more likely to enter academia and significantly less likely to enter the business sector. Their salaries reflect this, as there was a wage gap between men and women scientists. In the more detailed analyses of both job-credential match and job type, women scientists were more likely than men scientists to secure post-secondary teaching position rather than managerial positions.

Although the gender findings were unexpected, these findings were superseded by other demographic factors, most of which differed from my hypotheses, summarized in Figure 2. Although women scientists were slightly less likely to find a job credential match than men scientists as per my first hypothesis, marital status, the presence of

children and minority status were not associated with job-credential matches. The age of the scientist was associated with having a job-credential match, but in the opposite direction from what I expected. Older scientists were less likely to be employed in their field of doctoral study. Although scientists will accrue more human capital (experiences and training) as they age, perhaps this gives older scientists more options in the job market. Indeed, these scientists were more likely to be managers in a non-specified field. Naturalized citizens were actually less likely (not more likely) to have a job credential match than native U.S. citizens, and there existed no differences in having a job-credential match for non-U.S. citizen scientists compared to native U.S. citizens.

Table 7: Summary Table

| Summary Table | | | |
|---------------------------------------|--|-----------------------------|---------------------------------|
| Variable | Hypothesis (Likelihood of a Job-Credential Match) | Broad Field Findings | Specialty Field Findings |
| <i>Demographics</i> | | | |
| Gender | Men scientists will have a greater likelihood of a match than women scientists | ✓ | ✓ |
| Marital Status | Married scientists will be less likely to have a match than scientists who are not married. | X | X |
| Living with Children | Scientists who live with children will be less likely to have a match than those who do not live with children. | X | X |
| Minority Status | Minorities will be less likely to have a match than non-minorities. | X | X |
| Age | Older scientists will be more likely to have a match than younger scientists. | X | X |
| Citizenship | Non-U.S. citizens will be more likely to have a job credential match than native or naturalized U.S. citizens. | X | ✓ |
| <i>Human Capital</i> | | | |
| Field of First Doctorate | The field of first doctorate will be highly associated with a job-credential match. | ✓ | ✓ |
| Field of Bachelor's | The field of an individual's bachelor degree will not be associated with a job-credential match. | ✓ (Partial) | ✓ (Partial) |
| Hours Per Week Typically Worked | The more hours an individual works per week, the greater likelihood of a job-credential match. | X | X |
| <i>Social Capital</i> | | | |
| Attended Conferences in the Past Year | If a respondent attended a conference within the past year, they are more likely to have a job-credential match. | ✓ | ✓ |
| Number of Professional Memberships | The higher the number of professional memberships, the more likely a job-credential match. | ✓ | ✓ |

The human capital findings were similarly complex. Each field of doctoral study differed in rates of having a job-field mismatch as compared to Computer and Mathematical Sciences. Perhaps this is because Engineering and Computer and Mathematical Sciences comprise over 75% of the STEM workforce (National Science Board 2018). For the field of bachelor's degree, those with a degree in the Social and Related Sciences were more likely to find a job credential match. Perhaps the Social and Related Sciences are broad enough to encompass more jobs than the other fields. Although the findings reported here do not appear to support classic assumptions associated with Human Capital Theory, it is possible that the variables available in this survey do not adequately capture all possible forms of human capital. In other words, even though my models include some widely accepted human capital measures, alternate model specifications using a different set of human capital variables might produce a different set of findings. In contrast, findings do appear to support Social Capital arguments more directly. The social capital findings were straightforward and in line with my hypotheses and current research.

In addition, my analyses show that job outcomes are not just reflective of individual-level attributes. Employment sector had a significant association with being a job that matched the PhD field of study. Those in government jobs and in the business sector were significantly less likely to have a job in their field of study. This makes sense, as the comparison group is academia, and many scientists will choose to stay or are confined in their field of study, as the job categories outside of academia are less well defined. Salary had a nonlinear association, as those in the second quartile are more likely to find a job credential match and those in the top quartile are less likely to find a job

credential match. I suspect salary is highly correlated with job type, and this current association may reflect multicollinearity issues among the independent variables.

Teachers and Managers

Due to the limitations of operationalizing job/field matches, I parse out job type from job field among those without a credential match, and denote which scientists are more likely to be non-field-specific teachers or managers. Women scientists are more likely to be teachers than men scientists and men scientists are more likely than women scientists to be managers. The older a scientist is, the more likely they are to be in a manager position.

According to human capital theory, not only does the degree matter but also the field of study matters for job outcomes. The only field of doctoral study relative to Computer and Mathematical Sciences that increases the risk of becoming both a teacher and a manager is the Social and Related Sciences field. I presume that this is because this field teaches less technical skills and more comprehensive skills than the other fields, skills that would easily translate to a teaching or managerial position, as both require complex problem solving and people skills. Those who earn a doctorate in the Physical and Related Sciences are more likely to be managers and less likely to be teachers, but those scientists who earn their bachelor's in the Physical and Related Sciences are more likely to secure teaching positions. This discrepancy should be studied in further research

Limitations

This research is not without limitations. One limitation of the analysis is that I had to drop 4% of respondents from the sample –those who earned their doctorate in the ill-defined category of “Science and Engineering Related Fields”. Those respondents did

not have a way to clearly identify whether the job was in-field compared to other STEM fields. I instead focused on fields that were clearly defined to more clearly define the dependent variable, but these related fields are omitted from the analysis.

Another limitation is that these analyses are based on cross-sectional data, meaning the findings cannot be interpreted as the result of causal dynamics, but should instead be viewed as evidence of correlation. For example, managers have higher salaries than teachers, but possessing a high salary does not cause someone to be a manager. Similarly, government and business jobs do not employ teachers, and so that comparison is limited.

Although findings suggest only modest gender differences overall, that does not mean there are not gender differences that have not been explored. Based on current research about gender differences in STEM and in the work force (Acker 2006; Britton 2017), gender differences may also exist across the contextual variables. Due to the saliency of inequality regimes (Acker 1990b), it is possible that for men and women with jobs who have received a PhD degree within certain fields, men could face less resistance in securing a PhD credential match than women. Future analyses could use these findings and utilize gender as a modifying variable to explore whether the relationship of human and social capital characteristics varies for men and women on PhD job matches. Future research should also include an analysis of gender discrepancies between different PhD STEM fields in particular. Since the PhD STEM education system is already stratified (Fox and Stephan 2001) and there is a selection bias inherent in this sample, perhaps only solely looking at the PhD level (where women have already overcome many obstacles), is too narrow a focus. Future research should systematically explore gender as a modifying effect.

Along those same lines, my analyses were limited in exploring intersectional characteristics. For example, looking at women of color is difficult within these analyses because there are few women and fewer minorities in the. The racial distinctions within this data set is white/non-white, due to the constraints of the data and the small subset of scientists of color. Most of the non-whites are categorized as Asian non-Hispanic. This makes it exceedingly challenging to make clear inferences about intersectionality on a broad scale. Future research should investigate intersectional characteristics, such as gender and race, within the PhD realm.

Another limitation is the multicollinearity between the bachelor's degrees and doctoral fields of study. Furthermore, a subset of individuals in my study did not have any information on their bachelor's degrees. This could be explained by measurement error, but it could also mean some scientists skip earning their bachelor's degree and go directly into their master's or doctoral training. It could also mean that a scientist coming from another country has access to a different school-to-job pipeline. Future research should examine this phenomenon, as it could provide clues to why scientists leave their field of study, and to more thoroughly understand the mechanisms around the school to job pipeline.

Conclusion and Future Implications

My findings indicate support for the argument that job-credential matches are associated with both demographic characteristics, as well as social and human capital factors. Most noteworthy, 40-45% of scientists leave their field of doctoral study. My models account for *who* switches, but I can only speculate as to *why* they switch. It is unclear if this mass exodus is problematic or advantageous. Being an older scientist, for

example, is positively associated with holding a job outside of a field of study. This particular phenomenon could be explained by the accumulation of social and human capital – older scientists accrue social and human capital as they age, which perhaps gives them more job opportunities. Older scientists are also more likely to be in managerial positions, which may or may not be field specific. A job-credential mismatch in the case of older scientists could merely mean more opportunity, job mobility and access to a higher salary. A job mismatch could indicate a move to a higher salaried job, a job with higher satisfaction or to an interdisciplinary position.

On the other hand, for scientists who are less likely to switch fields, such as non-U.S. citizens, is a *match* actually *disadvantageous*? On the surface, the school-to-job pipeline is working for non-U.S. citizens (in line with Human Capital Theory). Non-U.S. citizens are less likely to switch their fields of study. Women are also more likely to find a job credential match. But higher salaries are associated with job credential *mismatches*, not matches. Jobs in the business sector are the highest paying industries and business sector jobs seem to be field specific. Perhaps we are seeing evidence of naturally occurring inequality regimes hidden in plain sight, as men are more likely than women to have a job mismatch, and more men than women are employed in the business sector. Even though certain groups of people are more likely to accrue a match, perhaps that match is less economically advantageous to them than a mismatch, as their opportunities for higher paying business jobs are limited. If certain demographic groups are systematically being limited from job mismatches, this would provide more evidence against Human Capital Theory and support the idea of inequality regimes. More research is needed to understand whether the problem lies within the pipeline of the doctoral field,

or whether the match/mismatch is a product of mobility. Research should also explore if matching education credentials to an occupational field is always best.

Although this particular dataset is not optimally suited to fully examine how institutional context counters HCT (since the institutional context were rough measures of institutional control, rather than prestige in a discipline or other institutional factors), more research should explore how institutional context plays a role in the school-to-labor force pipeline. Further, next steps should also look within this phenomenon and test gender interaction effects. In this way, future research can more fully explore inequality regimes at the institutional and individual levels.

A changing academic job market may also be changing the implications of a job-field mismatch. We assume a PhD recipient is a faculty member, but this is not the case with the changing academic context. As baby boomers exit their tenure-track academic positions at a slower pace, there are fewer jobs available for PhDs. The dwindling demand could mean academics receive less institutionalized support, which would propel PhD recipients to explore occupational opportunities outside of academia. Indeed, as this analysis shows, PhDs are employed in a wide range of sectors. The pipeline from a PhD to an academic position looks very different from the pipeline from a PhD to the business sector. Future research should compare and contrast the multiple occupational pipelines between sectors.

If so many PhD recipients are leaving their field of study, what does this mean about the training of the U.S. labor force? Should more fields be interdisciplinary? Are certain fields providing more transferable skills than other fields, which gives them an advantage in the labor force? As more PhD recipients enter the business or government

sectors, it would behoove doctoral granting institutions to assess their training and track their graduates through time. As academic jobs dwindle, it is important for institutions of higher learning to assess the market to better set their students up for occupational success. It would be useful for schools and students alike to understand how and when certain fields have specific prestige or are in high demand within the economic zeitgeist. Currently, the supply is mismatching demand. In either case, as many PhD scientists are leaving their field of study, future research should examine both the individual and contextual reasons as to why so many find themselves on separate field pathways.

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