

# **Predictors of Engineering Doctoral Students' Future Career Sector**

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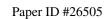
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### Abstract

Our research paper investigates the relationship between engineering graduate student funding, demographics, initial employment, and future career sector. Although a growing number of students have earned engineering doctorates over the past decade and over 10,000 students received engineering doctorates in 2015 (National Science Board, 2018a), there exists a gap in the literature regarding this student population. Unlike other STEM fields, where a doctoral degree serves as a key step in pursuing an academic path, engineering PhDs have a greater split between industry and academia, which we categorized as Industry and Education for future career sector. Students on Teaching Assistantships or Research Assistantships gain different experiences that may help them in different employment sectors. We categorized the five primary funding mechanisms as Research Assistantship, Fellowship, Teaching Assistantship, Personal Earnings, and Other. Initial Employment is categorized as Unemployed, Temporary, and Employed. Our research questions are:

- 1) What are the 3-year and 6-year career sector breakdowns for engineering doctoral recipients by gender and race?
- 2) How, if at all, do graduate student funding mechanism, gender and race, and initial employment predict future career sector 6 years after receiving an engineering doctorate?

Using NSF's Survey of Doctorate Recipients (SDR) and Survey of Earned Doctorates (SED) data, we analyzed relationships between engineering doctoral recipient primary funding mechanism and career sector at a timepoint of 5 to 6 years after receiving their degree. We matched populations between the two surveys and the resulting dataset consisted of 5682 engineering doctoral recipients who received their degrees between 1997 and 2014. We used descriptive statistics and step-wise logistic regression models with primary funding, gender and race, and initial employment as predictors to explore the research questions. Descriptive statistics indicate female students enter Education as a career sector in higher proportions than men 2 to 3 years after receiving their degree, while male students enter Industry in higher proportions than women. White, Asian, and International students are more likely to be employed in Industry 5 to 6 years after receiving their degree, while Black and Hispanic students are more likely to be employed in Education. The final logistic regression model with funding, gender and race, and employment type as predictors showed Hispanic, Asian, Temporary, and Employed as statistically significant. It is important to understand how student experiences in grad school prepare students for future careers and whether opportunities are presented equitably. Future work includes understanding student interests at the start and end of graduate school and whether funding type influences career goals and interests.

### Introduction

Graduate education is becoming an increasingly common pathway for career advancement and additional training in engineering. Over 10,400 engineering doctoral students received degrees in 2015, compared to slightly over 6,500 doctoral students in 2005 (National Science Board, 2018a). Compared to other STEM fields, engineering doctoral recipients have a greater split between industry and education. In 2013, 77% of engineering doctoral recipients were employed outside of academia 10 to 14 years post-doctorate completion, compared to 53% of life science doctorates, 63% of physical science doctorates, and 44% of mathematics/statistics doctorates (National Science Board, 2018b). Despite the growing number of engineering doctoral recipients, limited research focuses on this population and their future career trajectory. Existing higher education literature often focuses on graduate school solely as preparation for a future academic career (Austin, 2002; Austin & McDaniels, 2006; Burt, 2014; Saddler & Creamer, 2009; Saddler, 2013). However, a small but growing body of literature in STEM education emphasizes the role of industry in doctoral STEM student future career pathway and the need to prepare doctoral students for future industry careers (Fuhrmann et al., 2011; St. Clair et al., 2017; Watson & Lyons, 2011). Other research suggests that science and engineering graduate students still remain more interested in academic careers despite exposure to non-academic pathways (Gemme & Gingras, 2011).

Several studies have examined what leads graduate students to choose industry or academia as a career option, with personal preferences, such as "taste for science" or desired salary, shown to influence their decisions (Roach & Sauermann, 2010). Participation in internship programs during graduate study was found to allow life science students to make informed career choices (Schnoes et al., 2018). Students gain different experiences during graduate school through completing research or teaching assistantships that may help them in different employment sectors. Biomedical sciences doctoral students with research assistantships as their primary funding mechanism were found more likely to end up in jobs with high research activity than students with fellowships as their primary funding (Blume-Kohout & Adhikari, 2016). Faculty often view a focus on teaching as a distraction to their doctoral students' research activity. However, training in teaching does not decrease the research effectiveness of STEM doctoral students, as life science doctoral students trained in evidence-based teaching methods showed a slight increase in research confidence, communication, and publication (Shortlidge & Eddy, 2018).

Graduate students in the sciences reported that their advisors tended to promote academic careers over other options, while the graduate students themselves experienced a decreasing interest in academic careers over time (Sauermann & Roach, 2012). Additionally, women and minority STEM graduate students are often overrepresented in teaching or outreach roles for their primary source of funding (Thiry et al., 2007). Specific attention has been paid to the career decisions and trajectory of underrepresented graduate students in STEM fields (Jaeger et al., 2017; Carlone & Johnson, 2007). However, limited research has focused on the impact of employment type directly following graduate degree obtainment, particularly temporary post-doctoral positions, and the long-term effects of future career sector. To expand on existing literature and add to the current body of research, we are examining the predictors of and descriptive statistics related to future career sector of engineering doctoral recipients.

#### **Research Questions**

- 1. What are the 3-year and 6-year career sector breakdowns for engineering doctoral student by gender and race?
- 2. How, if at all, do graduate student funding mechanisms, gender and race, and initial employment predict future career sector 6 years after receiving an engineering doctorate?

## Methods

We gained access to previously administered national survey instruments and existing datasets on doctoral engineering students' primary funding mechanisms, demographic information, type of initial employment, and subsequent career sector at various timepoints. We cleaned the data before calculating descriptive statistics, such as chi-square tests and frequency statistics, and running a step-wise logistic regression model. The regression model predicts the future career sector of engineering doctoral recipients based on selected independent variables.

### Survey Instrument

We used two existing national datasets for our data collection. The Survey of Earned Doctorates (SED) is administered annually to all graduating doctoral recipients receiving research-based degrees, sponsored by the National Center for Science and Engineering Statistics (NCSES), the National Institutes of Health (NIH), the Department of Education, the Department of Agriculture, the National Endowment for the Humanities, and the National Aeronautics and Space Administration (NASA) (National Science Foundation, 2018b). Survey questions focus on experiences during doctoral degree attainment, demographic information, and immediate career plans following graduation. The Survey of Doctorate Recipients (SDR) is administered every two to three years to all graduates who have previously received a research-based doctoral degree in science, engineering, or health fields, sponsored by NCSES and NIH (National Science Foundation, 2018a). Survey questions focus on current and prior employment, any additional educational experiences, and demographic information. We received access to all SED and SDR survey data since the initial surveys were respectively administered in 1957 and 1973. We linked responses between the two surveys through participant ID number during our data analysis. We used select questions centering on doctoral student funding mechanisms, demographics, type of employment, and career sector during our analysis.

The dependent variables from the existing datasets are Career Sector at Year 5/6 and Career Sector at Year 2/3. We defined Career Sector as the type of employment held by the respondent at the time of the survey (SDR), categorized as Industry or Education. We categorized participants who were employed as private sector employees, either at for-profit companies or organization or at non-profit organizations, as working in Industry. Similarly, we categorized participants who were employed at educational institutions, including PK-12 schools, 2-year colleges, 4-year institutions, medical schools, and university-affiliated research institutes, as working in Education. We combined academic employment with other educational institution employment in Education and kept non-profit employment categorized as Industry to include all options for employment in the two Career Sector categories based on SDR survey questions. We removed U.S. government employment, including local, U.S. state, U.S. federal, and U.S. military service, as an option for career sector. There were not enough participants

working in government to run the logistic regression models, which is why we excluded them from analysis.

Independent variables include primary funding mechanism and type of initial employment. We defined primary funding mechanism (from SED) as the main source of financial support during graduate studies, categorized as Fellowship, Research Assistantship (RA), Teaching Assistantship (TA), Personal Earnings, or Other. While some students may receive multiple sources of funding throughout their time in graduate school, we concentrated on the primary source of graduate funding as the most impactful type of financial support. We defined type of initial employment (from SED) as the permanence of employment directly following graduation, categorized as Employed, Temporary, or Unemployed. Temporary employment refers to postdoctoral positions in industry/education or continued training during a traineeship or internship. Control variables include demographic information (from SED), such as Race and Gender. We categorized race as White, Hispanic, Black, Asian, and International while Gender is categorized as Male and Female. All participants categorized as White, Hispanic, Black, and Asian are domestic students.

#### Participants/Data Collection

Participants include engineering doctoral students who graduated with a doctorate between the years 1997 and 2014, completed the SED at time of graduation, and completed the SDR at least once at a timepoint zero to one years, two to three years, or five to six years following their doctoral attainment. Some participants included in the sample completed the SDR at multiple of the three specified timepoints (zero to one, two to three, and five to six years), while other participants completed the SDR at only one specified timepoint. We chose this range due to our focus on prediction of career sector at specific timepoints after graduation and the years that the SDR was administered. We are using SDR data collected from 2003 to 2015 to ensure an adequate sample size and maintain a sample of recent graduates. The total number of participants in the sample was 5682. Of the respondents who answered the SED demographic questions, 74% identified as male and 26% identified as female, and 33% identified as White, 6.0% as Asian, 3.1% as Hispanic, 4.0% as Black, and 54% as International (Table 1). The data was cleaned to remove domestic participants who identified as other than the four major racial categories, due to sample size considerations. Engineering majors included in the dataset are listed in Table 2, with the largest percentage of participants receiving electrical, electronics, and communications engineering, mechanical engineering, chemical engineering, biomedical and bioengineering, materials science engineering, or civil engineering degrees. While all participants attended universities located in the United States, data collection and analysis were not specific to any particular location or university type within the U.S.

| Gender (N = 5682) |    | Race (N = 5633) |     |
|-------------------|----|-----------------|-----|
| Male              | 74 | Hispanic        | 3.1 |
| Female            | 26 | White           | 33  |
|                   |    | Black           | 4.0 |

 Table 1: Demographic Breakdown of Total Participants

|  | Asian         | 6.0 |
|--|---------------|-----|
|  | International | 54  |

#### Table 2: Major Breakdown of Participant Total (%) (N = 5682)

| A anographical A attended to A attended   | 3.06  |
|---|-------|
| Aerospace, Aeronautical, & Astronautical  | 5.00  |
| Engineering                               | 1.10  |
| Agricultural Engineering                  | 1.18  |
| Bioengineering & Biomedical Engineering   | 8.41  |
| Chemical Engineering                      | 9.15  |
| Civil Engineering                         | 6.56  |
| Computer Engineering                      | 4.45  |
| Electrical, Electronics, & Communications | 20.73 |
| Engineering                               |       |
| Engineering Management & Administration   | 1.97  |
| Engineering Mechanics                     | 1.00  |
| Engineering Science                       | 1.04  |
| Environmental/Environmental Health        | 2.27  |
| Engineering                               |       |
| Geotechnical & Geoenvironmental           | 1.43  |
| Engineering                               |       |
| Industrial & Manufacturing Engineering    | 3.20  |
| Materials Science Engineering             | 6.95  |
| Mechanical Engineering                    | 11.03 |
| Nuclear Engineering                       | 1.27  |
| Ocean Engineering                         | 1.13  |
| Petroleum Engineering                     | 1.06  |
| Polymer & Plastics Engineering            | 1.28  |
| Structural Engineering                    | 3.94  |
| Systems Engineering                       | 1.64  |
| Transportation Engineering                | 1.99  |
| Engineering, Other                        | 5.24  |
| Data Analysis                             |       |

#### Data Analysis

We used R studio to perform descriptive statistics, such as frequency tests and chi-square statistical tests, and a step-wise logistic regression model. We ran frequency tests on the number of participants in each career sector at timepoints Year 5/6, Year 2/3, and Year 0/1. Additionally, we ran frequency tests on the gender and racial breakdowns in each career sector at Year 5/6 and Year 2/3. Chi-square tests were conducted for each of the gender and racial breakdowns in career sector at Year 5/6 and career at Year 2/3 to determine statistical significance in the different categories. A step-wise logistic regression model was conducted, for a total of three separate logistic regression models. Model 1 contains the demographic control variables of race and gender. Model 2 adds the independent primary funding mechanism variables to Model 1, and Model 3 adds the independent employment type variables to Model 2. Career sector at Year 5/6 is the dependent variable for each logistic regression model. Participants remained in the sample

data despite missing responses to survey items, noted when our logistic regression models and chi-square data have different N values.

Several variables were dummy coded for the statistical analysis. Career sector was dummy coded as 0 for Industry and as 1 for Education for each timepoint (Year 5/6, Year 2/3, and Year 0/1). Gender was dummy coded as 0 for male and 1 for female. Each race category (White, Hispanic, Black, Asian, & International) was dummy coded as 0 if that race was not selected and 1 if that race was selected. Similarly, each funding mechanism (Fellowship, RA, TA, Personal Earnings, & Other) was dummy coded as 0 if that funding mechanism was not selected and 1 if that funding mechanism was selected. Employment type (Employed, Temporary, & Unemployed) followed that same pattern, dummy coded as 0 if that employment type was not selected and as 1 if that employment type was selected. The reference category for each variable in the step-wise logistic regression model is as follows: RA (funding mechanism), White (race), Male (gender), and Unemployed (employment type).

#### Results

### **Descriptive Statistics**

Table 3 shows the percentage of participants in the industry or education career sectors at timepoints of Year 5/6, Year 2/3, and Year 0/1 following doctoral engineering degree attainment. At Year 5/6 after graduation, 69% of participants were in the industry sector and 31% in the education sector (N = 2788). At Year 2/3, 67% of participants were in the industry sector and 33% in the education sector (N = 2950). At Year 0/1, similarly, 67% of participants were in the industry sector and 33% in the education sector (N = 2950). At Year 0/1, similarly, 67% of participants were in the industry sector and 33% in the education sector (N = 279). The participants differ across the three different timepoints. Table 4 shows the gender breakdown for career sector at Year 5/6 and at Year 2/3. Chi-square analyses were run for gender across each timepoint. Career sector differed across gender at Year 2/3,  $\chi^2$  (1, N = 2950) = 5.47, p = 0.019, while career sector did not differ across gender at Year 5/6,  $\chi^2$  (1, N = 2838) = 1.78, p = 0.18. At Year 5/6, there was no statistical difference between future career sector by gender. At Year 2/3, men tended to be in the industry career sector in higher proportions that women, and women tended to be in the education career sector in higher proportions than men.

Table 5 shows the racial breakdown for career sector at Year 5/6 and at Year 2/3. Chisquare analyses were run for race across each timepoint. Career sector differed across race at Year 5/6,  $\chi^2$  (4, N = 2761) = 10.11, p = 0.00386, while career sector did not differ across race at Year 2/3,  $\chi^2$  (4, N = 2937) = 0.4278, p = 0.915. At Year 5/6, White, Asian, and International participants tended to be in the industry career sector and Black and Hispanic tended to be in the education career sector more frequently. At Year 2/3, there was no statistical difference between future career sector by the five designated racial categories. All participants were more frequently in the industry career sector at this timepoint.

Table 3: Participants (%) in Career Sector at Different Timepoints

|                     | Industry | Education |
|---------------------|----------|-----------|
| Year 5/6 (N = 2788) | 69       | 31        |

| Year 2/3 (N = 2950)  | 67 | 33 |
|----------------------|----|----|
| Year $0/1$ (N = 279) | 67 | 33 |

Table 4: Gender Breakdown (%) for Career Sector at Different Timepoints

|                      | Industry | Education |
|----------------------|----------|-----------|
| Year 5/6             |          |           |
| Male $(N = 2162)$    | 69       | 31        |
| Female ( $N = 676$ ) | 67       | 33        |
| Year 2/3             |          |           |
| Male (N = 2165)      | 68       | 32        |
| Female ( $N = 785$ ) | 64       | 36        |

Table 5: Racial Breakdown (%) for Career Sector at Different Timepoints

|                              | Industry | Education |
|------------------------------|----------|-----------|
| Year 5/6                     |          |           |
| White (N = 970)              | 70       | 30        |
| Hispanic $(N = 74)$          | 64       | 36        |
| Black ( $N = 122$ )          | 62       | 38        |
| Asian (N =179)               | 78       | 22        |
| International ( $N = 1416$ ) | 69       | 31        |
| Year 2/3                     |          |           |
| White $(N = 910)$            | 66       | 34        |
| Hispanic ( $N = 86$ )        | 70       | 30        |
| Black ( $N = 120$ )          | 70       | 30        |
| Asian $(N = 178)$            | 67       | 33        |
| International ( $N = 1643$ ) | 67       | 33        |

### Logistic Regression Models

Table 6 shows the three models resulting from our step-wise logistic regression analysis. Asian is a statistically significant predictor of career sector at Year 5/6 across in Model 1 (Demographics) and Model 3 (Demographics + Funding Mechanism + Employment Type). The  $\beta$ -coefficient for Asian increases in magnitude from Model 1 ( $\beta$  = -0.42) to Model 3 ( $\beta$  = -0.57). Hispanic becomes a statistically significant predictor in Model 3 ( $\beta$  = 0.57). After the addition of funding mechanism as a predictor, Model 2 has Fellowship as a statistically significant independent variable ( $\beta$  = 0.24). After the addition of employment type as a predictor, Model 3 contains Temporary and Employed employment as statistically significant independent variables. The sample size varies across the 3 models, as follows: Model 1 has 2744 participants, Model 2 has 2712 participants, and Model 3 has 2137 participants. The null model contains 2788 participants. The three models have different sample sizes due to missing responses to survey items. The reference variables across the three models are Male (gender), White (race), Research Assistantship (funding mechanism), and Unemployed (employment type).

In Model 1, with the demographic control variables of race and gender, gender is not statistically significant and does not predict career sector at Year 5/6. The race variable of Asian  $(p \le 0.05)$  is a statistically significant predictor of career sector at Year 5/6, and the total variance  $(R^2)$  in career sector explained by the demographic model is 0.9%. In Model 2, with the addition of funding mechanism as an independent variable, Fellowship (p < 0.05) is a statistically significant predictor of career sector at Year 5/6. The total variance  $(R^2)$  in career sector at Year 5/6 explained by Model 2 (Demographics + Funding Mechanism) is 3.3%. The addition of funding mechanism independent variables increased the total variance  $(R^2)$  in career sector explained by the model by 2.4%. In Model 3, with the addition of employment type as independent variables, Hispanic ( $p \le 0.05$ ), Asian ( $p \le 0.05$ ), Temporary ( $p \le 0.001$ ), and Employed ( $p \le 0.01$ ) are statistically significant predictors of career sector at Year 5/6. The total variance  $(R^2)$  in career sector at Year 5/6 explained by Model 3 (Demographic + Funding Mechanism + Employment Type) is 26.5%. The addition of employment type independent variables increased the total variance  $(R^2)$  in career sector explained by the model by 23.2%. Between the three models, employment type explains the largest variance in career sector at Year 5/6.

In Model 3, participants identifying as Hispanic ( $\beta = 0.57$ ) were more likely to end up in the Education career sector at Year 5/6, and participants identifying as Asian ( $\beta = -0.57$ ) were more likely to end up in Industry. Participants identifying as Hispanic were 80% more likely to end up in the Education career sector rather than Industry (odds ratio of 1.8), while participants identifying as Asian were 44% more likely to end up in Industry (odds ratio of 0.56). Additionally, participants with temporary employment lined up at graduation (Temporary) were more likely to end up in the Education career sector at Year 5/6 ( $\beta = 0.61$ ), while participants with permanent employment lined up (Employed) were more likely to end up in the industry sector ( $\beta = -0.50$ ). Participants with Temporary employment type were 80% more likely to end up in Education (odds ratio of 1.8), while participants designated as Employed (permanent employment) were 39% more likely to end up in Industry (odds ratio of 0.61). We ran logistic regression models with interaction terms between funding mechanism and employment type, demographics and employment type, and demographics and funding mechanism. The models are not included here because the significant interactions did not directly answer our research questions and do not add much in terms of our second research question.

| Null = 2788   | Model 1 | N = 2774   | Model 2 | N = 2712   | Model 3 | N = 2137   |
|---------------|---------|------------|---------|------------|---------|------------|
|               |         |            |         |            |         |            |
| Variable      | В       | Odds Ratio | В       | Odds Ratio | В       | Odds Ratio |
| Intercept     | -0.87   | 0.41***    | -0.97   | 0.38***    | -0.84   | 0.43***    |
| Female        | 0.11    | 1.1        | 0.11    | 1.1        | 0.13    | 1.1        |
| Hispanic      | 0.28    | 1.3        | 0.29    | 1.3        | 0.57    | 1.8*       |
| Asian         | -0.42   | 0.66*      | -0.37   | 0.69       | -0.57   | 0.56*      |
| Black         | 0.32    | 1.4        | 0.26    | 1.3        | 0.22    | 1.3        |
| International | 0.037   | 1.0        | 0.095   | 1.1        | 0.012   | 1.0        |
| Fellowship    |         |            | 0.24    | 1.3*       | 0.22    | 1.2        |

 Table 6: Logistic Regression Models

| ТА               |        | 0.26  | 1.3  | 0.26  | 1.3    |
|------------------|--------|-------|------|-------|--------|
| Personal         |        | 0.12  | 1.1  | 0.22  | 1.3    |
| Earnings         |        |       |      |       |        |
| Other            |        | -0.11 | 0.90 | 0.036 | 1.0    |
| Temporary        |        |       |      | 0.61  | 1.8*** |
| Employed         |        |       |      | -0.50 | 0.61** |
| $R^2$ (McFadden) | 0.0092 | 0.033 |      | 0.265 |        |

 $p \le 0.05, p \le 0.01, p \le 0.001$ 

#### Discussion

Demographics, particularly race, have a relationship with future career sector and primary funding mechanism. Through our analysis, we found that female engineering doctoral recipients are more likely to stay in the education sector, and men are more likely to go into industry. White, Asian, and International graduates are more likely to be employed in industry, while Hispanic and Black graduates tend to stay in education. Race, funding mechanism, and initial employment type all serve as predictors of career sector five/six years after graduation in the three Models. Hispanic, Asian, Temporary employment (i.e., postdocs), and Employed were all statistically significant predictors in our final logistic regression model, with Hispanic and Temporary predicting the education career sector and Asian and Employed predicting the industry career sector. Employment type explained the largest variation, while Temporary employment type has the largest  $\beta$ -coefficient ( $\beta = 0.61$ ).

While graduate education literature has previously focused on the career decisions and trajectory of STEM doctoral students (Roach & Sauermann, 2010; Carlone & Johnson, 2007; Jaeger et al., 2017), there has been limited research on specific predictors of future career sector of STEM doctoral students. This study adds to the limited body of work by running quantitative models with a population dataset to predict future career sector of engineering doctoral recipients. Limited attention has been paid to factors that may help graduate students achieve their career goals or hinder their ability to obtain employment in a certain career sector. All three constructs that we examined in our logistic regression model (Demographics, Funding Mechanism, and Initial Employment Type) were statistically significant in predicting career sector 5/6 years following graduation, although Employment Type explained the majority of variance in the model. This has important implications in how we discuss graduate education, particularly in what funding opportunities are provided for engineering doctoral students and what preparation and guidance they receive during the job application process.

It is important to further examine why race (Hispanic and Asian) is a statistically significant predictor of career sector in the logistic regression model and why gender and race differed across future career sector in our descriptive statistics. The race descriptive statistics showed no statistical significance in career sector at Year 2/3, while White, Asian, and International graduates were more likely to be in Industry and Black and Hispanic graduates in Education at Year 5/6. Since the participants were not the same at the two timepoints, we cannot draw conclusions about whether underrepresented groups are leaving industry after a few years from this data. However, the culture of education and industry may play a role in what types of

employment individuals choose to seek or remain in following degree attainment, with underrepresented groups in engineering more likely to choose the education sector. Our findings align with those of DeCuir-Gunby et al. (2013), who found that several Latina and African-American women faculty in academia chose that path due to challenges experienced while working in industry. Similarly, the National Academies of Science, Engineering, and Medicine (2018) recently released a report on issues of sexual harassment that women in STEM experience in academia and industry. We need to seek to understand if the culture of industry is only serving the needs of dominant groups in engineering and whether the education sector provides a more welcoming environment.

The assignment of funding opportunities should also be considered due to their statistical significance in the logistic regression Model 2 (Fellowship), since certain opportunities may prepare or interest students in a specific career sector. Graduates with Fellowships as their primary funding mechanism were predicted to be employed in the Education sector at Year 5/6 in Model 2. Our findings echo those of Blume-Kohout & Adhikari (2016), in that experiences gained through funding may impact future career pathways. However, it is unclear whether students are self-selecting into certain types of funding and career sectors due to their own interests or if the system is selecting for them and potentially restricting access to future careers. Since some faculty promote research experiences over other types of funding mechanisms (i.e., teaching) (Shortlidge & Eddy, 2018), the system may shape access to and interest in specific careers for developing graduate students. Additionally, we need to ensure that certain demographic groups are not disproportionately ignored from specific funding opportunities (Thiry et al., 2007), since funding impacts future career sector.

Additionally, we should continue to change the conversation about future careers with engineering doctoral students to include non-academic options, as the majority of students will find long-term employment outside of education (National Science Board, 2018b) and their first job after graduation has an impact on career sector. In the logistic regression model, Temporary and Employed were both statistically significant for predicting career sector at Year 5/6. Initial employment in a Temporary role predicted employment in the Education sector at Year 5/6, while initial employment in a permanent Employed role predicted employment in Industry. While somewhat intuitive that initial employment will predict future employment, there are important implications in how career pathways are discussed during graduate school. Since graduate school advisors tend to promote academic careers over other options (Sauermann & Roach, 2012), students may not be receiving information about other career opportunities and have to seek out that information themselves. They may also feel pressure to take roles that do not match their interests from their advisors or due to lack of knowledge about other career opportunities.

### **Conclusion & Future Work**

This study expands the current body of work on engineering doctoral recipients and their future employment following degree obtainment. Future work should focus on similar quantitative predictive models and descriptive statistics of career sector for other STEM disciplines, such as the physical sciences, life sciences, and mathematics. This study solely

focused on engineering as a discipline. Different timepoints after degree obtainment should be examined for each discipline, and we should consider longitudinal data to see how career trajectory of STEM doctoral recipients changes over time. The data in this study between Year 2/3 and Year 5/6 contained different participants, so we were not able to make conclusions about how career sector changed over time. Qualitative interviews would provide more information about how graduate student career aspirations changed over time, related to the experiences they gain through their funding. Additional attention should focus on the role of postdoctoral positions both in industry and academia on engineering doctoral career advancement. Education was categorized for all positions within academia and K-12 employment. Future work should involve looking at what types of positions graduates obtain within Education, such as tenure-track faculty positions or lecturer or other part-time positions.

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## References

- Austin, A.E. (2002). Preparing the next generation of faculty: Graduate school as socialization to an academic career. *The Journal of Higher Education*, 73(1), 94 122.
- Austin, A.E., & McDaniels, M. (2006). Preparing the professoriate of the future: Graduate student socialization for faculty roles. In: Higher Education: Handbook of Theory and Research, Volume 22, p 397 456.
- Blume-Kohout, M.E. & Adhikari, D. (2016). Training the scientific workforce: Does funding mechanism matter? *Research Policy*, 45, 1291 1303.
- Burt, B. (2014). *The influence of doctoral research experiences on the pursuit of the engineering professoriate* (Doctoral dissertation, University of Michigan).
- Carlone, H.B. & Johnson, A. (2007). Understanding the science experiences of successful women of color: Science identity as an analytic lens. *Journal of Research in Science Teaching*, 44(8), 1187 1218.
- DeCuir-Gunby, J.T., Grant, C., & Gregory, B.B. (2013). Exploring career trajectories for women of color in engineering: The experiences of African American and Latina engineering professors. *Journal of Women and Minorities in Science and Engineering*, 19(3), 209 -225.
- Fuhrmann, C.N., Halme, D.G., O'Sullivan, P.S., & Lindstaedt, B. (2011). Improving graduate education to support a branching career pipeline: Recommendations based on a survey of doctoral students in the basic biomedical sciences. CBE – Life Sciences Education, 10, 239 – 249.

- Gemme, B., & Gingras, Y. (2011). Academic careers for graduate students: A strong attractor in a changed environment. *Higher Education*, 63, 667 683.
- Jaeger, A.J., Mitchall, A., O'Meara, K.A., Grantham, A., Zhang, J., Eliason, J., & Cowdery, K. (2017). Push and pull: The influence of race/ethnicity on agency in doctoral student career advancement. *Journal of Diversity in Higher Education*, 10(3), 232 – 252.
- National Academies of Sciences, Engineering, and Medicine. (2018). Sexual Harassment of Women: Climate, Culture, and Consequences in Academic Sciences, Engineering, and Medicine. Washington DC: The National Academies Press.
- National Science Board. (2018a). *Science & Engineering Indicators 2018*. Retrieved from: https://www.nsf.gov/statistics/2018/nsb20181/report/sections/higher-education-in -science-and-engineering/graduate-education-enrollment-and-degrees-in-the-united -states#s-e-doctoral-degrees
- National Science Board. (2018b). *SEH Doctorates in the Workforce, 1993 2013*. Retrieved from: https://www.nsf.gov/nsb/sei/infographic2/?yr=2013&fd=Mathematics%20and%20 statistics&cs=None#main
- National Science Foundation. (2018a). *Survey of Doctorate Recipients*. Retrieved from: https://www.nsf.gov/statistics/srvydoctoratework/
- National Science Foundation. (2018b). *Survey of Earned Doctorates*. Retrieved from: https://www.nsf.gov/statistics/srvydoctorates/
- Roach, M. & Sauermann, H. (2010). A taste for science? PhD scientists' academic orientation and self-selection into research careers in industry. *Research Policy*, *39*, 422 434.
- Saddler, T., & Creamer, E. (2009). Socialization to the professoriate through research collaboration: Examining what engineering doctoral students aspiring to faculty careers can leave from faculty members. Paper presented at the American Society of Engineering Education, Austin, TX.
- Saddler, T. (2013). Socialization to research: A qualitative exploration of the role of collaborative research experiences in preparing doctoral students for faculty careers in education and engineering (Doctoral dissertation, Virginia Tech).
- Sauermann, H. & Roach, M. (2012). Science PhD career preferences: Levels, Changes, and Advisor Encouragement. *PLoS ONE*, *7*(5).
- Schnoes, A.M., Caliendo, A., Morand, J., Dillinger, T., Naffiziger-Hirsch, M., Moses, B.,
  Gibeling, J.C., Yamamoto, K.R., Lindstaedt, B., McGee, R., & O'Brien, T. (2018).
  Internship experiences contribute to confident career decision making for doctoral students in the life sciences. *CBE Life Science Education*, 17, 1 14.
- Shortlidge, E.E. & Eddy, S.L. (2018). The trade-off between graduate student research and teaching: A myth? *PLoS ONE, 13*(6).

- St. Clair, R., Hutto, T., MacBeth, C., Newstetter, W., McCarty, N., & Melkers, J. (2017). The "new normal": Adapting doctoral trainee career preparation for broad career paths in science. *PLoS ONE*, 12(5), 1–19.
- Thiry, H., Laursen, S.L., & Liston, C. (2007). (De)valuing teaching in the academy: Why are underrepresented graduate students overrepresented in teaching and outreach? *Journal of Women and Minorities in Science and Engineering*, *13*, 391–419.
- Watson, J. & Lyons, J. (2011). Aligning academic preparation of engineering PhD programs with the needs of industry. *International Journal of Engineering Education*, 27(6), 1394 1411.