# Socioeconomic Mobility into the Elite Professional Class:

## Differing Roles of Human, Social, & Cultural Capital Between Industries

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#### **Abstract**

The current discussion on increasing class stratification and social class reproduction focuses largely on underprivileged students securing positions in universities, but few studies look into socioeconomic mobility from higher education into the elite class (Haveman and Smeeding 2006; Rivera 2016). Do students in elite universities from different socioeconomic (SES) backgrounds have the same likelihood of securing elite employment regardless of their socioeconomic background? What role does the inter-generational transfer of social, cultural, and human capital play in job outcomes? In a time of decreased social mobility, examining the porous nature of elite class boundaries holds especial relevance. This study examines how undergraduate students from different socioeconomic backgrounds secure positions within the elite professional class. Using data collected from 460 Dartmouth senior students between February 10 to April 8, 2019, findings suggest that systematic forms of capital account for differences in employment by students of different socioeconomic classes. The first model suggests that socioeconomic class does predict selective post-graduate employment outcomes. The second model illustrates how the role of a parent's professional background and social capital have significant effects on finance, consulting, and technology employment outcomes. This study debunks the image of a meritocratic elite higher education system that enables equal access to prestigious employment opportunities and illustrates the mechanisms by which mobility is achieved.

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The meritocratic American dream implies that if students work hard enough and are bright enough, they can secure a better future for themselves. Literature on this topic has largely focused on underprivileged students securing positions in universities, but few studies look into socioeconomic mobility from higher education into the elite class (Haveman and Smeeding 2006; Rivera 2016). For those select few low socioeconomic background students who are accepted to and attend elite universities, how accessible and through what mechanisms is upward mobility achievable?

The employment outcomes of low socioeconomic status students in elite higher educational institutions may seem irrelevant to the vast majority of working class Americans. However, graduates of these elite universities are recruited into elite professions that offer distinct implications. First, the entry level salary places these new graduates in the top 10 percentile of household income. Increasingly, researchers cite the top ten percent of the income distribution as disproportionately increasing its wealth and driving inequality (Leonhardt 2019; Stewart 2018; Saez 2018). Second, these entry level positions pave careers into powerful government and corporate positions (Kalfayan 2009). As socioeconomic mobility becomes increasing limited, decision-making power over policies and resources will become increasingly stratified and inaccessible to underprivileged groups. Rivera and Tilcsik (2016) consider elite professional services as the contemporary gateways to the U.S. economic elite. Therefore, we should be interested in how social class reproduction and increasing class stratification occurs within elite higher education institutions.

This study provides several new contributions to the existing body of research. Previous literature has only determined that students of differing SES backgrounds utilize their time while in elite higher education institutions differently (Walpole 2003). For example, Walpole identifies that low SES students work jobs for more hours and higher SES students go to more office hours. This study would evaluate the consequences of those different time investment and capital-gaining college strategies in terms of how they affect post-graduate plans. Although previous hiring studies have established the role of discriminated demographics, human capital, social capital, or cultural capital separately, no existing research has constructed an empirical model to evaluate all of Bourdieu's forms of capital within an elite setting (Bourdieu 2018). This would be the first empirical

model that comprehensively captures each of these forms of capital at work in an elite hiring setting. This project also shows different industry employment outcomes by socioeconomic class, and explains away most of the variation in the initial model using Bourdieu's social reproduction theory variables (Bourdieu 2018). Finally, given the rise of the technology industry as a competitor for top talent, this project also expands the scope of Rivera's work to include the technology industry as well.

This study finds that, as hypothesized, students from higher SES backgrounds achieve selective employment at much higher rates than students from less-privileged background. In addition, human, social, and transferred parent capital all served as mechanisms that mediated selective employment outcomes. Contrary to the meritocratic view, human capital, represented by cumulative grade point average (GPA), played varying levels of importance depending on the industry. GPA had the strongest effect on securing employment in the consulting industry while having no significant effect on finance employment outcomes. Social capital that is leveraged for pre-professional help had a significant effect in finance and consulting, but not technology. Cultural capital that captures for highbrow or "bougie" hobbies accounts for some variation in outcomes within the consulting and technology industries. Finally, transferred parent capital, operationalized as having a parent in the same industry, had the strongest effect within the technology industry. This study debunks the facade of a meritocratic pipeline allowing upward mobility from elite higher education institutions to elite professions and illustrates how rigid class boundaries are even for the "best" students.

## **Literature Review**

There is very little empirical research on the mechanisms of mobility in elite higher education institutions. Walpole first studied how students of different SES backgrounds spend their time differently within these institutions (Walpole 2003). In the past, researchers have presented hiring decisions as stemming from an interviewee's human capital, such as concrete skills, and social capital, their social connections. Lauren Rivera recently published the first systematic empirical research on the

role of culture in hiring for elite professional services (EPS) employment by semantically analyzing 120 interviews and sending out experimental resume audits with cultural capital class signals (Rivera 2016; Rivera and Tilcsik 2016). Related qualitative studies that investigate the role of cultural capital in educational/employment outcomes refer heavily to theory originally provided by Bourdieu. Bourdieu's social reproduction theory conceptualized different forms of inherited capital and their role in maintaining class stratification through education and employment (Goddard 2003; Tzanakis 2011).

## **Social Reproduction via Higher Education**

American society tends to extol hard work and intellect as the ultimate means of social mobility (Rivera 1978). If educational success and admissions to higher education is truly meritocratic, then how do we account for the vast gap in higher education participation between students from the bottom and top quartiles of income (Trusts 2012). This phenomenon is the product of social reproduction, in which social classes stay constant within families from one generation to the next. For example, elite boarding schools are notorious for brokering unusual opportunities to attend elite universities. Persell and Cookson (1985) show that these boarding schools confer special rights onto their students through non-cognitive personality traits that make them more fit for admissions. Although these schools primarily consist of the status quo elite, they accept a few students from low socioeconomic backgrounds in order to established the outward appearance of a meritocratic process.

In the same way, we can expect that elite universities put on a facade of meritocratic admissions while brokering unusual opportunities for their students to achieve elite, high-status careers. In Rivera's book, Pedigree, she defined elite careers as the highest paying entry level jobs, which include top-tier investment banks, management consulting firms, and law firms (2). She also identifies that since she began her project in 2006, Wall Street has earned a poor reputation following the financial crisis. Meanwhile, the technology industry gained traction, began to compete for top talent, and offers greater salaries and stock options (279).

## The Role of Social, Cultural, and Human Capital in Upward Mobility

Research shows that wealthy and educated parents specifically enable their children's success through different forms of capital. Bourdieu's social reproduction work theorizes that parents endow their children with physical, human, social, and especially cultural capital that confer educational and occupational advantages. We will first explain the relevant types of capital, which include economic capital, human capital, cultural capital, social capital. We will then relate Bourdieu's (2000) concepts to explain how existing social class structure can be reproduced and solidified through the family via cultural capital.

Capital manifests in the family structure in a variety of manners. For example, family wealth becomes a form of economic capital for the child to inherit. Economic capital plays an especially important role in distinguishing children with elite families from children with educated, middle class families. For example, inherited economic capital enables elite children to develop expensive in-group behaviors, such as having financially exclusive hobbies and clothing brands. In an university environment, signaling elite in-group status symbols can facilitate elite underclassmen in being mentored by elite upperclassmen. Furthermore, an abundance of inherited economic capital systematically allows elite students to pursue more rewarded time investment strategies instead of working part-time while in university. The role of economic capital in educational disadvantages, however, is well-documented. Therefore, a student's family income will be accounted for in this study as a component of the primary independent variable, socioeconomic class.

Bourdieu also extensively discusses the role of social capital. Social capital concretely helps realize outcomes that would not have otherwise been possible by "facilitating certain actions by certain actors within a social structure" (Coleman 2000). An important role of social capital involves the transmission of information via social relationships. Information provides basis for action, such as knowing how to prepare for interviews or how to gain entry to exclusive networking events. However, students who have similar experiences, cultural values, and upbringing will tend to become friends because of homophily. Coleman (2000) theorizes that this closure of social networks exists in order to maintain social structures of obligations and expectations. Many previous studies have

managed to capture the effects of social capital on both educational outcomes and employment outcomes, but they do not sufficiently explain the full variation in hiring outcomes (Goddard 2003; Pager and Shepherd 2008). Coleman's social capital theory (1990) will inform the construction of a variable that captures both the structural and functional aspect of social capital. In other words, the variable should not just assess a person's assess to social capital but also whether they leveraged that capital.

More abstractly, the elite class's preference for in-group culture is the underlying premise for why cultural capital plays such a big role in upward mobility. Cultural capital is, at best, vaguely defined as "the sum total of investments in aesthetics, codes, and practices" or "transmissible parental cultural codes and practices capable of securing a return to their holders (Tzanakis 2011). Collins' (1971) theory on educational stratification and disparities in job outcomes explains that high status groups construct employment requirements to monopolize the available opportunities through their cultural standards. As a result, the exclusion of people who lack in-group culture is legitimized and normalized, when in reality these non-cognitive personality traits have nothing to do with meritocratic skill and ability (Bourdieu and Passeron 1990; Collins 1971; Bourdieu and Passeron 1977). Cultural capital plays a role even at the educational level, in which high-brow culture is rewarded by educators and this pedagogic pattern pattern serves as "a form of 'symbolic violence' forcing [working class or minority pupils] into a competitive mechanism that rewards only dominant cultural capital (Tzanakis 2011; Bourdieu and Passeron 1977). Rivera's recent study is the first to empirically confirm through analyzing interviews (n = 120) that culture serves as a vehicle for labor market sorting. According to her qualitative investigations, many interviewers would rank "culture fit", as determined by leisure activities, shared experiences, and self-presentation as the most important quality. Many interviewers cited the "airplane test", which refers to whether the interviewer thinks they would enjoy eating dinner, working late, or hanging out with the job candidate given the long-hours of the job. The airplane test is used most commonly in the consulting industry followed by finance industry. In a separate study, Rivera identified empirical effects of high-brow culture signals through a resume audit, holding all other factors on the resume constant

(Rivera and Tilcsik 2016). One resume signal Rivera used to operationalize higher social class was different sports teams, in this case sailing versus track and field. She found that the higher class resume received law firm interviews at a 16.25 percent rate as compared to 1.28 percent for the lower class resume, controlling for gender and identical academic achievements.

## Other Mechanisms Inhibiting Socioeconomic Mobility

We know that elite and non-elite students tend to operate differently as a result of differing parental tactics. Sociologist Annette Lareau outlined two commonly used methods of parenting (Lareau 2011). More privileged parents tend to practice "concerted cultivation", in which they treat their children as strategic projects. These privileged parents will nurture their children through structured extracurricular activities and intervene in their failures by advocating for better grades or learning resources. Meanwhile, less privileged parents tend to practice "natural growth", a belief that children thrive from the freedom to develop on their own and choose activities of interest. These differences often result in privileged children who know to ask for more help and seek preparation resources. Meanwhile, less privileged students may expend more energy and time in order to attain similar grades at the expense of gaining social or cultural capital available through oncampus extracurricular activities. Therefore, their efforts may not further their careers goals given the surprising lack of importance that academic merit holds in certain interview selection processes (Rivera 11).

Those non-elite students, operationalized here as low and middle socioeconomic students, who do gain elite cultural and social capital might achieve extreme upward mobility. Non-elite students can acquire the disposition and cultural habits of the elite class (e.g. international travel, expensive dining habits, etc.) by socialization into the mainstream elite culture (Coleman 2000). Furthermore, habitus likely plays a huge role in explaining what non-elite students think is possible in terms of future employment. Walpole mentions the proposition that associating with people who originate from a different background to adjust one's habitus is most accessible in college (Walpole 2003). Meanwhile, Horvat suggests that low SES students can learn to make choices that could facilitate

social mobility on a college campus (Horvat 2001). In either manner, non-elite students who adjust their habitus to elite standards and acquire elite cultural capital, can make choices that result in socially mobility and possibly break the cycle of social reproduction (Collins 1971).

## **Hypotheses**

In this study, we will adapt Rivera's definition of elite employment to include top-tier finance firms, management consulting firms, and technology companies. This definition of elite employment encapsulates the three primary industries that enable those with an elite undergraduate degree to solidify their economic position in the top 10 percent of U.S. income distribution.

We first need to establish that there is currently less achievement of selective employment by students of lower socioeconomic background within our sample in order to study the mechanisms behind it. We therefore hypothesize that:

H1: Differences exist in the selectivity of post-graduate outcomes among undergraduates from different socioeconomic backgrounds within elite higher education institutions. Specifically, students from lower socioeconomic backgrounds achieve selective employment at lower rates than the middle and high socioeconomic background students.

In order to empirically and comprehensively test each component of Boudieu's social class reproduction theory, this study will assess the role of each form of capital by itself and then combined.

H2a: Human capital mediates the effect of socioeconomic class on obtaining elite jobs. More specifically, higher human capital, measured by GPA, predicts a higher likelihood of obtaining any elite employment.

H2b: Social capital mediates the effect of socioeconomic class on obtaining employment in elite professional services industries. Specifically, higher social capital predicts a higher likelihood of obtaining elite professional services employment.

H2c: Cultural capital mediates the effect of socioeconomic class on obtaining an elite professional services employment outcome.

H2d: Transferred parent capital within an industry mediates a students employment in that same industry post-graduation.

As Rivera mentioned, students from elite universities are majoring in Computer Science and/or entering the technology sector at increasing rates due to higher compensation and more relaxed hours. The technology industry competes with traditional elite professional services for talent. However, the technology industry also touts itself as a more meritocratic and therefore accessible industry that allows technically competent talent from any university background to secure a position.

First, our analysis attempts to what role the different forms of capital cited in Bourdieu's social class reproduction theory play within each industry in comparison to other non-elite jobs (Bourdieu 2018). This analysis uses other jobs as the reference group in order to highlight which mechanisms each elite industries uses to uphold or loosen existing class boundaries. The following inquiries are phrased as research questions given that there is less theoretical literature on the technology industry to substantiate specific hypotheses.

RQ1: Within the finance, consulting, and technology industries, which forms of capital play a larger role in securing employment in each industry compared to other non-elite employment?

## **Data & Methods**

## **Participants**

This study collected data from the senior class at Dartmouth College. Dartmouth may seem like an insular outlier within Ivy League institutions from which to measure elite socioeconomic mobility. However, the College is actually an especially excellent population to focus on elite employment

outcomes. Many finance and consulting firms are considered elite employers that hire at a highly selective rate (1 percent) and only actively recruit from Ivy League or comparable universities. Within those universities, Dartmouth is highly over-represented given its small size in many elite firms. On average over the last three years, 26 percent, 19.3 percent, and 14.3 percent of Dartmouth graduates will begin working in the finance, consulting, and technology industries, respectively (Dartmouth 2018). Furthermore, more than half of the 2019 graduating class applied to the same top-tier elite professional service firm, which provides greater validity to any commonalities we find between those who are hired and are not (for Professional Development 2017).

The data on the Dartmouth senior class of 2019 was collected through a survey instrument fielded by Qualtrics. The Dartmouth College Committee for the Protection of Human Subjects approved this study and the survey instrument (study 00031481), as well as later modifications to the incentive structure. Participants were recruited via an e-mail on February 10, 2019 that advertised a survey about their time at Dartmouth for a \$10 Amazon gift card. Two waves of e-mail reminders were sent out to participants who had not yet completed the survey as of February 26th and April 2nd, 2019. The researcher was able to collect e-mails for 950 out of the total 1115 members in the class of 2019. About 3 percent of recruitment e-mails bounced back because students had transferred or dropped out. 460 of the e-mailed respondents took the survey which resulted in a 49.9 percent response rate. Of those 460 respondents, 395 respondents fully completed the survey and were therefore retained in our final analytical sample. I

The Dartmouth class of 2019 cohort size consisted of 1115 students as of 2015 (Seamen 2015). Demographically, the sample collected for this project does not accurately mirror the overall Dartmouth undergraduate in that it is more female (59.5 percent), more white (49.89 %), and more Asian-American (32.65 %). Cohort-level specifics were not available for the Class of 2019, but certain statistics indicate that some of the anomalies are due to year-to-year cohort variation. For example, The Dartmouth newspaper mentioned that the Class of 2019 has the largest percentage

<sup>&</sup>lt;sup>1</sup>The compensation was originally set at \$5, but an error led us to bump the amount to \$10. However, the institutional review board was not concerned about overpay given the overall wealth of this demographic. In fact, this new survey rate nearly doubled the response rate.

of Asian-Americans, at 19.6 percent, which partially explains the over-representation of Asian-Americans in this sample (Asoulin 2015). Similarly, the first generation students were underrepresented in this survey as they accounted for only 7.59 percent of the total survey sample, compared to 14 percentage of the total class of 2019.

This sample bias can be partially explained by the fact that respondents dropped out at disproportionate rates amongst key demographics. In general, students who dropped out were disproportionately male, queer, and very low or high income. The researcher received feedback from some male and/or high SES students that the 10 minute survey was too long or not worth the compensation. Underprivileged students who completed the survey indicated that the survey reminded them of their "low social status", which could be a key reason for dropout amongst underprivileged populations. Therefore, even though this data collection captured half of the cohort there may be significant sample bias if these same highly privileged and highly underprivileged dropout/non-respondent populations tend to disproportionately represent the high-paying employment and unemployed outcomes.

## **Survey Design and Procedure**

Once participants consented to participate, they proceeded through eight sections. They first completed questions about their basic demographics and parents' employment as well as educational background. Then, respondents filled out their Dartmouth academics, post-graduate plans, weekly time investment strategies. Following this, they provided multiple select answers to various campus organization involvement questions meant to capture cultural capital. Respondents then selected from multiple select choices what forms of pre-professional help they received, as well as who helped them. These questions were meant to capture social capital. The survey ended with an open-ended grid for students to fill out any extra-curricular groups they were involved in and what role of leadership they held, as well as what they did during each of their term-long breaks away from campus. Specifically, it asked for the organization they spent their time with and their position, if applicable. This extensive survey of 69 questions led to higher participant dropout, but

also allowed us to capture the nuanced mechanisms by which social reproduction occurs. The full instrument is provided in Appendix A.

However, in the pursuit to capture nuanced latent variables, questions to measure components of capital ended up taking a more exploratory form. Furthermore, previous pilot study showed that people had averse reactions to be asking point-blank whether they had gone into finance or consulting. This led to the realization that the intentions of the survey should be less transparent so as to improve the user experience of the survey by decreasing feelings of judgment through what respondents perceive as narrow outlooks on their employment outcomes. Overall, even though the survey was a little longer than necessary, the response rate was much higher than the 2018 pilot survey, especially given the lower compensation. Survey testers who took the survey instrument reported back a median completion time of 10.5 minutes, which was then relayed to respondents within the recruitment e-mail.

Next, we asked respondents to select which bracket their cumulative GPA falls within, how many academic citations they have received, as well as what they majored and minored in. Respondents then divulged what their post-graduate plans include (e.g. employment, graduate school, undecided). Those who selected employment were funneled into selecting the industry they would be working within. To determine the selectivity of their employment, we then asked them to tell us what company or organization they will be working for after graduation as well as what other employment offers they received. We qualitatively coded this information based on online reports of prestige within each industry as well as graduate schools to determine the selectivity of their post-graduate plans. Finally, we asked respondents whether they had ever applied to an internship or job in finance or consulting, as well as technology, in order to control for their interest in a field.

The next section asked students a battery of questions about their extra-curricular commitments to try to identify cultural capital. Respondents answered a series of questions about their Greek house affiliation, senior secret societies, varsity sports, club sports, cultural affinity groups, and study abroad programs. We then asked them how many extracurricular activities they have meaningfully participated. The survey then conditionally provided a grid with that number of activity

slots. Students could delineate each activity in an open-ended slot and rank their involvement on a scale (e.g head of leadership, other leadership, highly involved member, less involved member). Finally, students were briefly debriefed on the last page.

## 1.1 Analytic Strategies: Variable Construction

#### **Principle Component Analysis**

Principle Component Analysis (PCA) was used to create the social and cultural capital index. PCA is a technique used to reduce the dimension of our feature space. The researcher was able to extract features using PCA, in which we combined our input variables to produce new variables that are independent of each other. This method was chosen for its ability to reduce the number of variables in the model to conserve power. Furthermore, long sets of questions fielded all attempted to capture the same two latent variables: social and cultural capital. PCA assisted in identifying relationships between the answers to these sets of questions.

After the original categorical responses to these questions were loaded into the function, different eigenvalues for each variable were returned, along with the amount of variance explained by each dimension. The first two dimensions in the search for both social and cultural capital explained slightly over 60 percent of the variation. Each dimension ranked how much each variable contributed to the variation in that direction. These dimensions are orthogonal to the other dimensions that become variables, so as to avoid confounding variables in the regression. In the measures section, the social and cultural capital index variables were constructed in this manner by exporting the top two dimensions that accounted for 60 percent of variation as index variable.

#### Measures

#### **Dependent Variables**

The two key dependent variables utilized in the analysis are selectivity of post-graduate plans and employment industry. The selectivity of a student's post-graduate plans was collected based on open-ended responses. This data was qualitatively coded as an ordinal variable using strict guide-

lines for employment and graduate school. Students who had at least one offer at a selective company or graduate school were coded as the highest value, while those with at least one offer at a selective company, graduate school, or research position were coded as the middle value, and all unemployed or undecided students were coded as the lowest value. The cut-off for highly selective companies was determined using the top 15 most prestigious consulting firms according to Consulting.com, the most prestigious 25 firms for finance according to Vault, and the "Big 5" for technology (See Appendix B).

Meanwhile, the dependent variable of employment industry was captured using a multiple select question with suggested industry options. Students who indicated in the previous question that they planned to enter graduate school or research were coded as missing in this sample. Then, all industries aside from finance, consulting and technology (technical roles only) were collapsed into "other" to serve as the reference group. The reason for isolating finance, consulting, and technology are that they are the key industries that systematically recruit undergraduates from elite universities and pay near a 6-figure salary, which helps us answer our question on how students are achieving socioeconomic mobility through entering elite professions. Other high-status elite professions such as law or medicine were left out of this operationalized variable due to further graduate school requirements. In fact, key groups within the "other" category include students entering healthcare (9.44 percent) and government/public policy roles (11.16 percent).

Table 1: Descriptive Statistics of Model Variables

	N	Proportion or Mean	SD	Min	Max
Selective Post-graduate	338	0.75	0.83	0 = No Plans	2 = Selective Plans
Employment Industries	338				
Finance		12.72%			
Consulting		24.56%			
Technology		15.68%			
Other		31.68%			
Unemployed		15.36%			
Gender	395				
Male		39.49%			
Female		59.49%			
Non-binary		1.01%			
Race	389				
White		49.87%			
Black		4.88%			
Latino		6.94%			
Asian		32.65%			
Native		3.86%			
Pacific Islander		1.80%			
Annual Family Income	386				
<\$35k		9.07%			
\$35k - \$74k		9.07%			
\$75k - \$99k		8.81%			
\$100k - \$129k		16.84%			
\$150k - \$199k		15.03%			
\$200k - \$349k		15.28%			
\$350k - \$629k		10.36%			
\$630k+		12.44%			
Father Education	392				
High school diploma or less		15.93%			
Some college or 2-year degree		3.13%			
4-year college degree		21.93%			
Masters, PhD, or M.D.		34.73%			
J.D. or M.B.A.		24.28%			
Mother Education	392				
High school diploma or less		10.71%			
Some college or 2-year degree		11.22%			
4-year college degree		30.10%			
Masters, PhD, or M.D.		33.93%			
J.D. or M.B.A.		14.03%			
Cumulative GPA	392	6.54	1.72	1 = (< 2.00)	10 = (3.92+)
Matching Parent Industry	395	0.29	0.45	0 = Not Matching	1 = Matching
Social Capital Index 1	395	0.00	1.00	-1.50	3.88
Social Capital Index 2	395	0.00	1.00	-3.17	2.56
Cultural Capital Index 1	394	$^{14}0.00$	1.00	-2.06	1.34
Cultural Capital Index 2	394	0.00	1.00	-2.06	1.34

## 1.2 Key Independent Variable

This study's key independent variable is socioeconomic class, frequently abbreviated as SES class. A major problem in studying elites and elite institutional spaces are that typical definitions of socioeconomic class do not suffice in capturing who experiences disadvantages and privileges. Therefore we constructed a unique SES class variable by using the family income, mother education, and father education data collected about each participant in the survey.

Institutionally, Dartmouth provides free tuition to students whose families earn under \$100k per year, possessing typical assets (Financial Aid 2015). This clearly indicates that a family income under this threshold confers some type of disadvantage within this elite higher education space. Furthermore, first generation students have been shown in a lot of literature to experience systematic disadvantages as well (Wilbur and Roscigno 2016). This study's definition of SES class classifies either of these groups as low socioeconomic status, referred to as Low SES. Meanwhile, on the upper-end, about a quarter of Dartmouth undergraduates come from families with annual incomes in the top 1 percent of the nation (Aisch 2017). Therefore, we operationalized the high socioeconomic status group, high SES, as any student whose family income exceeds \$350k. The remaining students who have at least one college-educated parent and whose family earns between \$76k - \$349k are considered mid SES in this study, even though they are considered the 90th to 98th percentiles of the income distribution nation-wide. The cut-offs chosen for the annual family income question do not align with the New York Times' definition of wealth, but do match those used by the Dartmouth Office of Greek Life (Leonhardt 2019). This choice was made to ensure better data collection given that in the pilot study, a number of students over the \$350k family income cut-off could not pinpoint their income in narrower categories.

## 1.3 Other Independent Variables

The other independent variables we measured or constructed are meant to capture the mechanisms that Rivera and Bourdieu suggest play an instrumental role in securing elite professions. The three

Table 2: Socioeconomic Class Definitions

SES Class	Pct.	Definition
Low SES	22.28%	Family income <\$75k or
		first-generation college student
Mid SES	55.44%	Family income \$76 - \$349k and
		at least one college-educated parent
High SES	22.28%	Family income >\$350k

latent mediating mechanisms that we hope to capture are human capital, social capital, and cultural capital (Bourdieu and Passeron 1990). In order to achieve this, the model includes the following two categorically measured independent variables: cumulative grade point average (GPA) and parent professional degree/industry background. Then, the researcher asked qualitative coders with professional experience in their respective industries to rate relevant work experience along a strictly defined five-point scale, resulting in a relevant work experience variable. A social capital index variable was constructed using a set of questions measuring how participants leveraged social connections for professional gains, as well as who these connections were. The researcher qualitatively coded the multiple select data on Greek life, varsity sports, club sports, as well as open-ended text on hobbies into ordinal values to capture cultural fit in an index as well.

#### **Human Capital**

Cumulative Grade Point Average (GPA) is most critical measure of human capital used in the models. Cumulative GPA was captured through a multiple choice question. The seemingly arbitrary cut-off points were determined along honors lines to help distinguish excellence in an institution with grade inflation. The top four cut-off points capture summa cum laude (top 5 percent), Phi Beta Kappa (top 10 percent), magna cum laude (top 15 percent), and cum laude (top 35 percent).

Relevant work experience was also gathered but as a human capital component. Three students who are highly involved in pre-professional organizations and on-campus recruiting qualitatively graded open-ended text entries on a scale of 1 to 5. The ordinal values were assigned as follows: student has no work experience (=1), irrelevant work experience to industry (=2), irrelevant but selective experience (=3), relevant industry experience (=4), relevant and highly selective industry

experience (=5).

Bourdieu and Rivera showed that a parent's professional expertise conveys both cultural and transferred human capital onto students. This study operationalized parent capital as matching parent background. Conditional on a students final employment industry, we coded matching parent background as true if at least one parent has previously worked in this industry or attained a degree directly related to this field. For example, a student entering finance whose parent worked in finance as well or attained an MBA would qualify as a match. Students who entered other industries and had no parents working in the finance, consulting, and technology industry were also coded as a match. Those students with who went into other industries but had at least one parent in finance, consulting, or technology were coded as not a match.

Extensive parent demographic questions asked respondents about their parents' highest educational degree as well which fields they obtained any undergraduate and graduate degrees. Respondents also selected industries that their mother and father have worked in, given that suggests parents are able to confer employment advantages onto their children within their industry.

#### **Social Capital Index**

Initially, six questions were fielded to help capture the role of social capital in a pre-professional context. Respondents were asked to answer "how many people have helped guide you in a meaningful or significant way in your personal, college, and pre-professional life?", as well as select how they knew these mentors. The multiple select choices for how they became socially connected included: parent, sibling, family friend, Dartmouth upperclassmen, Dartmouth same-year peer, Dartmouth alumni, Center for Professional Development, Faculty, supervisor, or co-worker. Respondents then identified how many people they could ask for help finding an internship or job at the beginning of college, and then again during their junior fall. Finally, respondents were asked to select which of the following six forms of professional help they had when finding an internship or job: interview practice, specialized information, resume edits, recommendation, referral, and reference. The next page logically conditioned on these answers. For each form of help they received, they were asked to identify how they knew this person from the same social connection options as aforementioned.

This set of questions meant to capture both the potential connections a person had as well as how they converted them into professional gains, per Coleman's social theory (1990).

Table 3: Social Capital Methodology

	EIG1	EIG2	Qualitative Definitions
After College: Internship Help	6.74	0.05	Number of people respondent could ask for help
Before College: Internship Help	17.67	79.10	in finding an internship or job from after college. Number of people respondent could ask for help in finding an internship or job from
Family Help Utilized	4.54	0.13	before the start of college Count of number of times participant asked parents, family friends, or siblings
Institutional Help Utilized	61.50	19.80	for help in obtaining professional leverage* Count of number of times participant asked faculty, upperclassmen, or college peers
Leverage Number of Mentors	6.51 3.03	0.92 0.02	for help in obtaining professional leverage* Count of forms of professional leverage used Count of number of meaningful mentors

<sup>\*</sup>Professional leverage refers to help acquired in resume edits, referrals, recommendations, references, interview practice, or obtaining specialized information.

Therefore, the first social capital index variable captured how much help they had available and actually asked for in their search for an internship across. The second social capital dimension captures students with strong social capital before college to convert into professional gains, which correlated with those who tended to ask for more institutionally available help at Dartmouth.

#### **Cultural Capital Index**

Culture fit is a metric highly valued by interviewers in elite professional services jobs to determine whether a new employee will be "a suitable co-worker and playmate" (Rivera 2016). Although many qualitative studies have cited its importance, no study thus far has been able to capture its effects quantitatively outside of small cross-sectional samples (Tzanakis 2011). Therefore, this cultural capital index attempted to capture this latent variable of elite professional cultural capital.

Lamont points out that "shared culture within the classroom versus within interviews are not the same because culture is context specific (Lamont et al. 1992)." Therefore, the indicators of cultural

capital here must be adjusted for the Young Urban Professional lifestyle. The index incorporated two types of variables. One type captured a student's ability to culturally fit into mainstream, status quo elite Dartmouth spaces. The second captured a student's signal of "bougie" culture. The reason for this is that traditional sociological research focuses on high-brow culture that elites use to socialize with each other. In this case, we want to measure a student's ability to fit into the elite professional class rather than the true elite class. The elite professional class highly values bougie culture, which which often includes traveling, expensive foods, and bougie hobbies.

The eight questions addressing each student's participation in Greek affiliation, senior society, extra-curricular activities, varsity sports, club sports, study abroad programs, and previous attendance at a private high school were fielded to capture variables of cultural capital.

As Stevens (2008) mentioned, underlying taste and experience can be difficult to obtain or measure, given how subjective they are. This variable construction methodology refers to Rivera's recent work conducted on signals of high-brow culture on resumes. The qualitative coder looked only at leisurely activities that could not be used on a resume as work experience. In other words, hobbies or activities that have no bearing on job performance. The sports and hobbies were recoded into ordinal values indicating whether they were high-brow sports/hobbies, other sports/hobbies, and no sports/hobbies (Rivera and Tilcsik 2016). Greek houses were rated based on how much cultural fit they might indicate. Houses with a reputation for being highly desirable, highly affluent, or having many alumni connections in elite professions were rated as a high elite culture fit. Within the Greek selectivity variable, other houses were coded as a culture fit and unaffiliated students were coded as neutral culture fit. They were then re-coded into the following variables shown in Table 4.

Principle Component Analysis showed that studying abroad and attending a private high school did not map onto any highly significant dimensions of variation. This is likely because such a high proportion of students at the College and in the sample study abroad (41.98 percent) and attended a private high school (36.96 percent). The first two dimensions of principle component analysis explain 60 percent of the variation. The first index variable seemed to capture A (see appendix for

Table 4: Cultural Capital Methodology

	EIG1	EIG2	Qualitative Definitions
Greek	91.67	4.94	2 = Affiliated in high-status house, 1 = Affiliated, 0 = Not affiliated
Private School	7.39	0.11	<ul><li>1 = Private high school,</li><li>0 = Public or other high school</li></ul>
Bougie Sports	0.24	37.22	2 = Highbrow sports team, 1 = Sports team, 0 = No sports
Study Abroad	0.24	0.93	1 = Studied abroad, 0 = Did not study abroad
Bougie Hobbies	0.43	56.80	<ul><li>2 = Highbrow leisure activity, 1 = Leisure activity,</li><li>0 = No leisure activities</li></ul>

weighting). The second index variable seemed to capture B.

#### 1.4 Control Variables

#### 1.4.1 Gender

The survey collected gender as a categorical variable, with 1.01 percent of students falling into the non-binary category. Due to concerns about the size and power of each cell, we collapsed it into the binary variable of "female."

#### 1.4.2 Race

Due to the low representation of Black, Latinx, and Native American students in the sample, individual representations of these underrepresented minority groups was not possible. Meanwhile, Asian-Americans were over-represented in the sample, but are not considered a minority group in workforce recruiting. We therefore coded race into a categorical variable as "White", "Asian", and "Other."

Table 5: Employment in Industries by SES Class

0% 9.30°			19.85%
	701 (0.0.40)	<b>50</b> 400	50 00M
22% 60.47	7% 60.24%	58.49%	58.02%
70% 30.23	3% 22.89%	15.09%	22.14%
2 42	83	53	262

## 2 Analytic Strategy: Models

Within this study, two variations of logistic regression are used to determine a relationship between socioeconomic class and two different dependent variables that represent employment outcomes. Overall, the family of logistic regressions was chosen to best illustrate the effect of discrete capital-gaining choices or circumstances that are mutually exclusive alternatives.

## 2.1 Ordinal Logistic Regression

The ordinal logistic regression is used first for models involving an ordinal dependent variable. The strength of an ordinal logistic regression is that it describes data and explains the relationship between one dependent variable and more than two independent variables. In this case, socioeconomic class and all the various forms of capital are independent variables that are either ordinal or continuous, which satisfy the requirements of an ordinal regression.

Ordinal logistic regressions are often understood using odds ratios because the coefficients themselves are not interpretable. The coefficient represents the estimated increase in log odds of the outcome per unit increase in the value of the exposure. Therefore, the log odds is found through the exponential function of the regression coefficient. More importantly, odds ratio can be interpreted as the odds that an outcome will occur given a particular exposure, or independent variable, compared to the odds of the outcome occuring in the absence of that exposure. When odds ratio is equal to 1, exposure does not affect odds of outcome. When the odds ratio is greater than 1, exposure is associated with higher odds of outcomes. When the odds ratio is less than 1, exposure is associated with lower odds of outcome.

## 2.2 Multinomial Logistic Regression

Multiple logistic regression is similar to the ordinal logistic regression, except that the dependent variable is a nominal variable. In other words, none of the outcomes is ranked better than another, they are different but mutually exclusive groups. In this case, employment by industry is a nominal

variable and thus qualifies the second set of models for the multiple logistic regression. One downfall of the multinomial regression is that it requires a large sample size, which made finding results within this cross-sectional sample more difficult. For this reason, the analysis does not include an interaction between selectivity and industry, given that some of those interaction cells would be in the single digits.

One key difference involves the interpretation of the coefficient outcomes. Although the mathematical manner to interpret the coefficients (exponentiation) is the same as the ordinal logistic regression, the ratio of the probability of one outcome over the excluded baseline outcome is referred to as a risk ratio (RRR). The RRR indicates how the risk of the outcome falling in the comparison group compared to the risk of the outcome falling in the referent group changes with the variable in question. RRR >1 increases risk of outcome falling in comparison group relative to outcome falling in referent group. To avoid confusion, given that risk ratio has a negative semantic connotation and was developed in the context of medical procedures, this paper will frame all risk ratios as the odds on an outcome.

## **Results**

## Differences in Selective Employment by Socioeconomic Class

We find in the descriptive table below (Table 6) that low SES students enter selective employment at lower rates than both mid and high SES students and they are more likely to be unemployed. Proportional to their own socioeconomic class group, 17 percent of low SES students achieve highly selective employment as compared to 24 percent of mid SES and 25 percent of high SES students, respectively.

We then applied an ordinal logistic regression to see how well socioeconomic class (SES) predicts selective post-graduate plans. Consistent with H1, Table 7: Model 1 shows that differences in achievement of selective post-graduate plans between students of different SES backgrounds exist.

Table 6: Selective Employment by SES Class

	Low SES	Mid SES	High SES	Total
Not Employed	53	108	37	198
(Pct.)	60.23%	49.32%	42.05%	50.13%
Employed	20	58	21	99
(Pct.)	22.73%	26.48%	23.86%	25.06%
Selective	15	53	30	98
(Pct.)	17.05%	24.20%	34.09%	24.81%
$\overline{N}$	88	219	88	395
Total Pct.	100.00%	100.00%	100.00%	100.00%

High SES students had a 1.95 times higher odds (p < 0.05) of moving up a category in employment selectivity outcomes in comparison to low SES students. Similarly, middle SES students had a 1.71 higher odds of moving up a category in employment selectivity compared to low SES students (p < 0.05). This confirms the general wisdom that more privilege correlates with more employment opportunities.

Furthermore, consistent with H2a, Model 2 shows that cumulative GPA increases the odds of more selective employment by 18 percent (p = 0.002). No statistically significant difference remains in employment outcomes by SES class. Therefore, the effects of cumulative GPA, itself, are very instrumental in that it mediates the effect of class. In fact, a separate regression shows that a student that moves up one SES category has a 1.93 times higher odds of achieving a GPA in the next highest bracket (p < 0.001).

Consistent with H2d, Model 5 shows that having a parent with a matching industry background increases a student's odds of achieving a more selective employment outcome by 2.15 times with significance (p = 0.001). However, in Model 4, consistent with H2b, the first social capital index measure increases a student's likelihood of achieving more selective employment by 39 percent (p = 0.002) while the second index factor decreases a student's likelihood by 20 percent (p < 0.05).

Both cultural capital index variables in Model 3 had neutral to slightly positive effects on the odds ratio of selective employment, but neither was significant (p >.10). Therefore, we can neither reject nor accept H2c in which we hypothesized that cultural capital mediates class differences. In Model 4, consistent with H2b, the first social capital index measure increases a student's likelihood

of achieving more selective employment by 39 percent (p = 0.002) while the second index factor decreases a student's likelihood by 20 percent (p < 0.05). Consistent with H2d, Model 5 shows that having a parent with a matching industry background increases a student's odds of achieving a more selective employment outcome by 2.15 times with significance (p = 0.001).

Finally, when we look at the combination of all these capital variables in Model 6, we find that altogether having a parent in the industry has the most significant significant effect, representing a 1.85 times higher likelihood of selective employment (p = 0.01). The socioeconomic class effect of having a more selective employment outcome have been explained to a point where there is no more statistical significance and the coefficients indicate lower likelihood of achieving selective outcomes. This indicates that we may have overfit this combined model and that overall there is support for H2a, H2b, and H2d on the mediating effects of human capital.

Table 7: Odds Ratio of Selective Employment

	Mo	del 1	Мс	del 2		Model 3
SES Class (ref = Low)						
Mid SES	1.71*	(1.98)	1.31	(0.93)	1.41	(1.19)
High SES	1.95*	(2.09)	1.38	(0.89)	1.49	(1.14)
Female			0.89	(-0.56)	0.88	(-0.58)
Race (ref = White)						
Asian			1.18	(0.69)	1.33	(1.15)
Other			0.60	(2.33)	0.49	(-2.08)
Cumulative GPA			$1.18^{*}$	(2.33)		
Cultural Capital Index 1					1.17	(1.39)
Cultural Capital Index 2					1.04	(0.35)
Observations	338		333		333	

z statistics in parentheses, risk ratios used as coefficient

Selectivity outcome coded as an ordinal variable of Undecided, Employed, Selective Employment  $^+$  p < 0.10,  $^*$  p < 0.05,  $^{**}$  p < 0.01,  $^{***}$  p < 0.001

Table 8: Odds Ratio of Selective Employment

	Мо	del 4	Mod	lel 5	N	Model 6
Socioeconomic Class						
Mid SES	1.35	(1.05)	1.33	(1.00)	1.03	(0.10)
High SES	1.35	(0.83)	1.36	(0.87)	0.89	(0.30)
Female	0.92	(-0.40)	0.90	(-0.50)		(-0.00)
Race (ref = White)						
Asian	1.17	(0.64)	1.30	(1.08)	1.00	(0.81)
Other	$0.52^{+}$	(-1.86)	$0.52^{+}$	(-1.90)	0.78	(-0.68)
Cumulative GPA					1.25**	(2.96)
Social Capital Index 1	1.39**	(3.04)			1.38**	(2.90)
Social Capital Index 2	$0.80^{*}$	(-2.02)			$0.78^{*}$	(-2.14)
Cultural Capital Index 1					1.16	(1.26)
Cultural Capital Index 2					1.08	(0.72)
Parent in Industry			2.15***	(3.29)	1.85**	(2.58)
Observations	332		333		332	

z statistics in parentheses

Selectivity outcome coded as an ordinal variable of Undecided, Employed, Selective Employment  $^+$  p < 0.10,  $^*$  p < 0.05,  $^{**}$  p < 0.01,  $^{***}$  p < 0.001

However, the literature also suggests that employment outcome disparities should vary even more depending on the industry. This leads us to model consulting, finance, and technology, which are the three main industries that Dartmouth students exit into, in comparison to the remaining industries (Dartmouth 2018). This multinomial logistic regression approach will allow us to compare the differing effects of human, social, and cultural capital within each industry.

## **Employment Industry Differences**

The second portion of the findings centers around answering the research questions around differences in capital mechanisms between industries. Therefore, in the following models, employment industry serves as our primary outcome variable. We coded post-graduate plans into a nominal variable with four outcomes: finance industry, consulting industry, technology industry, and all other industries.

As we can see in the below Table 9, the descriptive statistics indicate that students of different socioeconomic backgrounds enter the finance, consulting, and technology at different rates. We once again set out to answer whether these differences can be explained by Bourdieu's various forms of proposed capital that uphold social class reproduction. Therefore, the model uses "Other" industries as a reference group in order to highlight the especial importance of social, cultural, and human capital of our three elite professions of focus in relation to other careers.

Table 9: Employment in Industries by SES Class

	Other	Finance	Consulting	Technology	Total
Low SES	24.10%	9.30%	16.87%	26.42%	19.85%
Mid SES	54.22%	60.47%	60.24%	58.49%	58.02%
High SES	21.70%	30.23%	22.89%	15.09%	22.14%
N	83	43	83	53	262

## 2.3 SES Class Differences are mediated by Structural Racism

After running a nominal logistic regression, we establish a the expected baseline class difference in Model 7. Those in the high SES class have a 4.47 times higher odds of entering finance than other industries (p = 0.015) compared to low SES students. Meanwhile those from the mid SES class have a 3.45 times higher odds (p = 0.030). If we switch over to examine consulting, we see a similar effect size for mid and high SES. Mid and high SES students have a 1.89 (p = 0.072) and 1.87 (p > .10) times higher odds of entering consulting, respectively, but with varying levels of significance. Finally when we look into the technology industry, we find that mid SES students have a 1.17 times higher odds than low SES students of entering the technology industry, without significance (p > .10). Meanwhile, high SES students actually are 21.4 percent less likely to enter technology compared to low SES students (p > .10).

This unique lower industry likelihood for the high SES students is partially driven by interest and not disadvantage. As high SES students had only a 1.36 times of applying to technology internships and jobs (p > .10) compared to low SES students, while this population simultaneously has a 4.14 times higher odds of applying to finance or consulting jobs (p < 0.001). Meanwhile, the mid SES students have a 2.16 times higher odds of applying to technology jobs (p < 0.01) and a 3.15 times higher odds of applying to finance or consulting jobs (p < 0.001) than low SES students. These findings were determined using a question fielded that asked students whether they had ever applied to an internship or job in technology and another question that asked the same about elite professional services (finance or consulting). We do not have data to confirm offers in technology. However, based on advantages that higher SES students have been shown to hold, such as higher cumulative GPA, we might hypothesize that they enter technology at a lower rate than low SES students by choice. Either they never apply to the technology industry to begin with, or they receive a finance or consulting internship and choose it over technology due to traditional prestige and lifestyle choices, given that the pay in technology actually beats elite professional services.

After establishing this expected baseline class difference in Model 7, the Model 8 finds that some of the previously established class differences lose their statistical significance when controlling for

gender and race. Those in the high SES class have a 3.99 times higher odds of entering finance than other industries (p = 0.036) compared to low SES students. Meanwhile those from the mid SES class have a 2.87 times higher odds (p = 0.075). If we switch over to examine consulting, we see a similar effect for mid and high SES, but without any statistical significance (p > 0.10). Mid and high SES students have a 1.52 and 1.46 times higher odds of entering consulting, respectively. Finally when we look into the technology industry, we find that mid SES students have a 1.24 times higher odds of entering the technology industry (p > .10) than low SES students. Meanwhile, high SES students have a 8 percent less likelihood of entering technology than low SES students (p > 0.10). Therefore, it seems that the class differences that seemed prevalent in finance and consulting were mostly explained by gender and race differences.

When we more carefully examine the effect of the controls in Model 8, we see that across industries women suffer in their likelihood to obtain a job in these elite professions as compared to another profession. Women have a 46.6 percent, 21.0 percent, and 58.3 percent less likelihood of entering finance (p < .10), consulting (p > .10), and technology (p < .01), respectively, compared to other industries. This however, does not explain the diminished class difference if we assume that roughly equal numbers of women and men are admitted within each socioeconomic class.

We next investigate the role of our second control, race, to find that the role of structural racism helps explain why some of the differences of class disappeared. For example, underrepresented minorities in elite professions, labeled here as "Other Races" are also much more likely to be low income and first generation at Dartmouth College. Within the consulting comparison, underrepresented minorities are 63.5 percent less likely to enter consulting with statistically significance (p < 0.05), which made the mid and high SES class advantage effect smaller and less significant. When we run a logistic regression to confirm this relationship, we find that underrepresented minorities have a 51.5 percent lower likelihood to not apply to elite professional services internships or jobs (p < 0.05) than white students when controlling for major class advantages. In this very same model, we see that when analyzing the role of race, a high SES and a mid SES background still account for a 3.64 times and 2.72 times higher odds (p < 0.001) than low SES students. This ancillary regres-

sion confirms the overall framing of our investigation as one around socioeconomic class and not race. While the effect of race is important and negatively affects black, latinx, and native american students, these effects are mostly mediated through structural class disadvantages.

Table 10: Odds Ratio of Employment by Industry

Cother Industries (ref.)   Finance Industry   Finance Industry   Finance Industry   Finance Industry   SES (ref = Low)   Finance Industry   SES (ref = Low)   Finance Industry   SES (ref = Low)   Finance Industry   Gammale		Mod	del 7	Mo	del 8	Mod	del 9	Mod	el 10
SES (ref = Low)         3.45°         (2.18)         2.87"         (1.78)         2.92"         (1.79)         2.47         (1.44)           High SES         4.47°         (2.43)         3.99°         (2.09)         4.10°         (2.11)         3.50"         (1.78)           Female         0.53*         (2.173)         0.53*         (2.17)         0.54         (2.17)         0.54         (2.17)         0.54         (2.17)         0.54         (2.17)         0.54         (2.17)         0.54         (2.17)         0.54         (2.17)         0.54         (2.17)         0.54         (2.17)         0.54         (2.17)         0.54         (2.18)         0.54         (2.18)         0.54         (2.18)         0.54         (2.18)         0.64         0.18         0.43         0.45         (2.18)         0.64         0.18         0.45         0.15*         0.21         0.18*         0.28         0.26         0.20	Other Industries (ref.)								
Mid SES         3.45*         (2.18)         2.87*         (1.78)         2.92*         (1.79)         2.47         (1.78)           High SES         4.47*         (2.43)         3.99*         (2.09)         4.10*         (2.11)         3.50*         (1.78)           Female         1.53         (1.07)         0.53*         (-1.75)         0.54         (-1.57)           Race (ref = White)         1.53         (1.07)         1.54         (1.07)         2.11         (1.64)           Other         1.60         0.40         (-1.35)         0.38         (-1.38)         0.45         (-1.15)           Cumulative GPA         1.80         0.45*         (-1.50)         0.15**         (-3.12)         0.18*         (-1.83)         0.26*         (-2.01)           Consulting Industry         1.89*         (-4.59)         1.52*         (-3.12)         0.18*         (-1.83)         0.26*         (-2.01)           Mid SES         1.89*         (1.80)         1.52         (1.11)         1.27         (0.62)         1.31         (0.62)           High SES         1.87         (1.48)         1.46         (0.83)         1.14         (0.28)         1.27         (1.51)           Other	Finance Industry								
High SES         4.47*         (2.43)         3.99*         (2.09)         4.10*         (2.11)         3.50*         (1.78)           Female         0.53*         (-1.73)         0.53*         (-1.75)         0.54         (-1.57)           Race (ref = White)         3.50*         (-1.73)         0.53*         (-1.75)         0.54         (-1.57)           Asian         1.53         (1.07)         1.54         (1.07)         2.11         (1.64)           Other         0.40         (-1.35)         0.38         (-1.38)         0.45         (-1.15)           Cumulative GPA         0.99***         (-4.59)         0.15***         (-3.12)         0.18**         (-0.26)         1.18         (0.41)           Constant         0.09****         (-4.59)         0.15***         (-3.12)         0.18**         (-1.83)         0.26**         (-2.01)           Consulting Industry         0.09***         0.15**         (-3.12)         0.18**         (-1.83)         0.26**         (-2.13)         0.26**         (-2.13)         0.26**         1.28         0.26**         (-2.01)         0.28**         0.28**         0.28**         0.28**         0.28**         0.26**         0.27**         0.47**         0.47** </td <td>SES <math>(ref = Low)</math></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>	SES $(ref = Low)$								
Female         Co.53*         (-1.73)         0.53*         (-1.75)         0.54*         (-1.75)           Race (ref = White)         Asian         1.53         (1.07)         1.54         (1.07)         2.11         (1.64)           Other         0.40         (-1.35)         0.38         (-1.38)         0.45         (-1.15)           Cumulative GPA	Mid SES	3.45*	(2.18)	$2.87^{+}$	(1.78)	$2.92^{+}$	(1.79)	2.47	(1.44)
Race (ref = White)         Asian         1.53         (1.07)         1.54         (1.07)         2.11         (1.64)           Other         0.40         (-1.35)         0.38         (-1.38)         0.45         (-1.15)           Cumulative GPA         v         -0.97         (-0.26)	High SES	4.47*	(2.43)	3.99*	(2.09)	4.10*	(2.11)	$3.50^{+}$	(1.78)
Asian Other         1.53         (1.07)         1.54         (1.07)         2.11         (1.64)           Other         0.40         (-1.35)         0.38         (-1.38)         0.45         (-1.15)           Cumulative GPA         1.87         (-1.59)         0.97         (-0.26)         1.88         (0.41)           Parent in Industry         0.09***         (-4.59)         0.15**         (-3.12)         0.18**         (-1.83)         0.26*         (-2.01)           Consulting Industry         0.09***         (-4.59)         0.15**         (-3.12)         0.18**         (-1.83)         0.26*         (-2.01)           SES Class (ref = Low)         1.89**         (1.80)         1.52         (1.11)         1.27         (0.62)         1.31         (0.62)           High SES         1.89**         (1.48)         1.46         (0.83)         1.14         (0.28)         1.27         (0.47)           Female         1.89**         (1.48)         1.46         (0.83)         1.14         (0.28)         1.27         (0.47)           Other         Other         0.32***         (-3.73)         0.47**         (-2.11)         0.58**         (-3.41)         0.94         (-0.90)	Female			$0.53^{+}$	(-1.73)	$0.53^{+}$	(-1.75)	0.54	(-1.57)
Other         0.40         (-1.35)         0.38         (-1.38)         0.45         (-1.15)           Cumulative GPA         10.97         (-0.26)         1.18         (0.41)           Parent in Industry         0.09***         (-4.59)         0.15***         (-3.12)         0.18**         (-1.33)         0.26**         (-2.01)           Consulting Industry         SES Class (ref = Low)         8         8         8         8         8         8         8         8         9         0.28**         9         0.02**         1.28**         0.02**         1.20**         0.02**         1.31         0.02**         0.02**         1.31         0.02**         0.02**         1.31         0.02**         0.02**         1.31         0.02** </td <td>Race (ref = White)</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>	Race (ref = White)								
Cumulative GPA         Parent in Industry         C.4.59         0.15**         C.3.12         0.18**         C-1.63         0.26**         C.2.01           Constant         0.09***         -(4.59)         0.15**         (-3.12)         0.18**         (-1.83)         0.26**         (-2.01)           Consulting Industry SES Class (ref = Low)         1.89**         (1.80)         1.52         U.1.11         1.27         (0.62)         1.31         (0.62)           Mid SES         1.87         (1.48)         1.46         (0.83)         1.14         (0.28)         1.27         (0.47)           Female         1.87         (1.48)         1.46         (0.83)         1.14         (0.28)         0.83         (-0.57)           Female         1.87         (1.48)         1.46         (0.83)         1.14         (0.28)         0.83         (-0.57)           Female         1.87         (1.48)         1.28         (0.76)         1.77         (1.51)           Other         6         1.33         (0.91)         1.28         (0.76)         1.77         (1.51)           Other         6         0.32**         (-3.13)         0.91         1.28         (0.76)         (-1.10)         0.94	Asian			1.53	(1.07)	1.54	(1.07)	2.11	(1.64)
Parent in Industry Constant         0.09***         (-4.59)         0.15**         (-3.12)         0.18**         (-1.83)         0.26**         (-2.01)           Consulting Industry SES Class (ref = Low)         8         1.89**         (1.80)         1.52         (1.11)         1.27         (0.62)         1.31         (0.62)           High SES         1.87         (1.48)         1.46         (0.83)         1.14         (0.28)         1.27         (0.47)           Female         1.87         (1.48)         1.46         (0.83)         1.14         (0.28)         1.27         (0.47)           Female         1.87         (1.48)         1.46         (0.83)         1.14         (0.28)         1.27         (0.47)           Female         1.87         (1.48)         1.46         (0.83)         1.14         (0.28)         0.83         (-0.57)           Race (ref = White)	Other			0.40	(-1.35)	0.38	(-1.38)	0.45	(-1.15)
Constant         0.09***         (-4.59)         0.15**         (-3.12)         0.18**         (-1.83)         0.26*         (-2.01)           Consulting Industry SES Class (ref = Low)         SES Class (ref = Low)         SES Class (ref = Low)         1.89**         (1.80)         1.52         (1.11)         1.27         (0.62)         1.31         (0.62)           High SES         1.87         (1.48)         1.46         (0.83)         1.14         (0.28)         1.27         (0.47)           Female         1.87         (1.48)         1.46         (0.83)         1.14         (0.28)         1.27         (0.47)           Female         0.79         (-0.82)         0.82         (-0.68)         0.83         (-0.57)           Race (ref = White)         1.33         (0.91)         1.28         (0.76)         1.77         (1.51)           Other         0.50         0.32***         -2.11         0.56         (-1.16)         0.42*         (-1.70)           Cumulative GPA         1.24         (-3.73)         0.47*         (-1.84)         0.08***         (-3.41)         0.98         (-0.04)           Tech Industry         5         5         5         5         5         5         5	Cumulative GPA					0.97	(-0.26)		
Consulting Industry SES Class (ref = Low)           Mid SES         1.89+         (1.80)         1.52         (1.11)         1.27         (0.62)         1.31         (0.62)           High SES         1.87         (1.48)         1.46         (0.83)         1.14         (0.28)         1.27         (0.47)           Female         0.79         (-0.82)         0.82         (-0.68)         0.83         (-0.57)           Race (ref = White)         0.79         (-0.82)         0.82         (-0.68)         0.83         (-0.57)           Race (ref = White)         0.83         (0.91)         1.28         (0.76)         1.77         (1.51)           Other         0.83         (-0.21)         0.56         (-1.16)         0.42+         (-1.70)           Cumulative GPA         1.31         (0.91)         1.28         (0.76)         1.77         (1.51)           Other         0.32***         (-3.73)         0.47+         (-1.84)         0.08***         (-3.41)         0.98         (-0.04)           Tech Industry         0.55         1.17         (0.43)         1.24         (0.53)         1.17         (0.37)         1.08         (0.15)           High SES         0.79	Parent in Industry							1.18	(0.41)
SES Class (ref = Low)         I.89+         (1.80)         1.52         (1.11)         1.27         (0.62)         1.31         (0.62)           High SES         1.87         (1.48)         1.46         (0.83)         1.14         (0.28)         1.27         (0.47)           Female         0.79         (-0.82)         0.82         (-0.68)         0.83         (-0.57)           Race (ref = White)	Constant	0.09***	(-4.59)	0.15**	(-3.12)	$0.18^{+}$	(-1.83)	0.26*	(-2.01)
Mid SES         1.89+         (1.80)         1.52         (1.11)         1.27         (0.62)         1.31         (0.62)           High SES         1.87         (1.48)         1.46         (0.83)         1.14         (0.28)         1.27         (0.47)           Female         0.79         (-0.82)         0.82         (-0.68)         0.83         (-0.57)           Race (ref = White)         3.33         (0.91)         1.28         (0.76)         1.77         (1.51)           Other         0.32***         0.37*         (-2.11)         0.56         (-1.16)         0.42+         (-1.70)           Cumulative GPA         1.31**         (2.95)         0.74         (-0.90)           Parent in Industry         (-3.73)         0.47+         (-1.84)         0.08***         (-3.41)         0.98         (-0.04)           Tech Industry         5         5         5         5         5         5         5         6         -0.04)         0.08***         (-3.41)         0.98         (-0.04)           Tech Industry         5         5         5         5         5         5         5         6         -0.24)         1.08         (0.15)           High SES <td>Consulting Industry</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>	Consulting Industry								
High SES         1.87         (1.48)         1.46         (0.83)         1.14         (0.28)         1.27         (0.47)           Female         0.79         (-0.82)         0.82         (-0.68)         0.83         (-0.57)           Race (ref = White)         3.33         (0.91)         1.28         (0.76)         1.77         (1.51)           Asian         1.28         (0.76)         1.77         (1.51)           Other         0.32***         (-2.11)         0.56         (-1.16)         0.42*         (-1.70)           Cumulative GPA         1.31 **         (2.95)         0.74         (-0.90)           Parent in Industry         0.32***         (-3.73)         0.47*         (-1.84)         0.08***         (-3.41)         0.98         (-0.04)           Tech Industry         0.32***         (-3.73)         0.47*         (-1.84)         0.08***         (-3.41)         0.98         (-0.04)           Tech Industry         0.42**         0.42**         0.42**         0.34**         0.34**         0.34**         0.34**         0.34**         0.34**         0.34**         0.04**         0.04**         0.04**         0.04**         0.04**         0.04**         0.04**         0.04**	SES Class (ref = Low)								
Female         0.79         (-0.82)         0.82         (-0.68)         0.83         (-0.57)           Race (ref = White)         1.33         (0.91)         1.28         (0.76)         1.77         (1.51)           Other         0.37*         (-2.11)         0.56         (-1.16)         0.42+         (-1.70)           Cumulative GPA         1.31 **         (2.95)         0.74         (-0.90)           Parent in Industry         0.32***         (-3.73)         0.47+         (-1.84)         0.08***         (-3.41)         0.98         (-0.04)           Tech Industry         SES Class (ref = Low)         0.42*         (-1.84)         0.08***         (-3.41)         0.98         (-0.04)           Mid SES         1.17         (0.43)         1.24         (0.53)         1.17         (0.37)         1.08         (0.15)           High SES         0.79         (-0.48)         0.92         (-0.15)         0.85         (-0.29)         0.86         (-0.24)           Female         0.42**         (-2.64)         0.42**         (-2.61)         0.36**         (-2.62)           Race (ref = Low)         1.85*         (1.65)         1.83         (1.61)         3.40**         (2.68) <t< td=""><td>Mid SES</td><td><math>1.89^{+}</math></td><td>(1.80)</td><td>1.52</td><td>(1.11)</td><td>1.27</td><td>(0.62)</td><td>1.31</td><td>(0.62)</td></t<>	Mid SES	$1.89^{+}$	(1.80)	1.52	(1.11)	1.27	(0.62)	1.31	(0.62)
Race (ref = White)         Asian       1.33       (0.91)       1.28       (0.76)       1.77       (1.51)         Other       0.37*       (-2.11)       0.56       (-1.16)       0.42+       (-1.70)         Cumulative GPA       1.31 **       (2.95)         Parent in Industry       0.32***       (-3.73)       0.47+       (-1.84)       0.08***       (-3.41)       0.98       (-0.04)         Tech Industry       SES Class (ref = Low)       V       <	High SES	1.87	(1.48)	1.46	(0.83)	1.14	(0.28)	1.27	(0.47)
Asian Other       1.33       (0.91)       1.28       (0.76)       1.77       (1.51)         Cumulative GPA       0.37*       (-2.11)       0.56       (-1.16)       0.42+       (-1.70)         Parent in Industry       1.31**       (2.95)       0.74       (-0.90)         Constant       0.32***       (-3.73)       0.47+       (-1.84)       0.08***       (-3.41)       0.98       (-0.04)         Tech Industry       SES Class (ref = Low)       Value	Female			0.79	(-0.82)	0.82	(-0.68)	0.83	(-0.57)
Other         0.37*         (-2.11)         0.56         (-1.16)         0.42+         (-1.70)           Cumulative GPA         Parent in Industry         1.31**         (2.95)         0.74         (-0.90)           Constant         0.32***         (-3.73)         0.47+         (-1.84)         0.08***         (-3.41)         0.98         (-0.04)           Tech Industry         SES Class (ref = Low)         Mid SES         1.17         (0.43)         1.24         (0.53)         1.17         (0.37)         1.08         (0.15)           High SES         0.79         (-0.48)         0.92         (-0.15)         0.85         (-0.29)         0.86         (-0.24)           Female         0.42**         (-2.64)         0.42**         (-2.61)         0.36**         (-2.62)           Race (ref = Low)         Asian         1.85*         (1.65)         1.83         (1.61)         3.40**         (2.68)           Other         0.67         (-0.78)         0.76         (-0.52)         0.73         (-0.54)           Cumulative GPA         1.08         (0.75)         (-0.42**)         (-0.42**)         (-0.42**)         (-0.42**)         (-0.42**)         (-0.52**)         0.73**	Race (ref = White)								
Cumulative GPA         Image: Cumulative GPA Parent in Industry         Image: Cumulative G	Asian			1.33	(0.91)	1.28	(0.76)	1.77	(1.51)
Parent in Industry         Constant         0.32***         (-3.73)         0.47+         (-1.84)         0.08***         (-3.41)         0.98         (-0.04)           Tech Industry         SES Class (ref = Low)           Mid SES         1.17         (0.43)         1.24         (0.53)         1.17         (0.37)         1.08         (0.15)           High SES         0.79         (-0.48)         0.92         (-0.15)         0.85         (-0.29)         0.86         (-0.24)           Female         0.42**         (-2.64)         0.42**         (-2.61)         0.36**         (-2.62)           Race (ref = Low)         1.85*         (1.65)         1.83         (1.61)         3.40**         (2.68)           Other         0.67         (-0.78)         0.76         (-0.52)         0.73         (-0.54)           Cumulative GPA         1.08         (0.75)         (-4.42)         (-4.42)         (-4.42)           Constant         0.32***         (-3.73)         0.42**         (-1.95)         0.26*         (-1.70)         0.27*         (-2.24)	Other			$0.37^{*}$	(-2.11)	0.56	(-1.16)	$0.42^{+}$	(-1.70)
Constant         0.32***         (-3.73)         0.47*         (-1.84)         0.08***         (-3.41)         0.98         (-0.04)           Tech Industry         SES Class (ref = Low)         8         8         8         8         8         8         9         9         9         9         9         1.17         (0.43)         1.24         (0.53)         1.17         (0.37)         1.08         (0.15)         1.08         (0.15)         1.08         (0.15)         1.08         (0.24)         1.08         (0.24)         1.08         (0.24)         1.08         (0.24)         1.08         (0.24)         1.08         (0.24)         1.08         (0.24)         1.08         (0.24)         1.08         (0.24)         1.08         (0.24)         1.08         (0.24)         1.08         (0.24)         1.08         (0.26)         1.08         (0.26)         1.08         (0.26)         1.08         (0.75)         1.08         (0.75)         1.08         (0.75)         1.08         (0.27)         (0.24)         1.08         (0.27)         (0.27)         (0.24)         1.08         (0.75)         1.08         (0.27)         1.08         (0.27)         1.08         (0.27)         1.08         (0.27)         1.08 </td <td>Cumulative GPA</td> <td></td> <td></td> <td></td> <td></td> <td>1.31 **</td> <td>(2.95)</td> <td></td> <td></td>	Cumulative GPA					1.31 **	(2.95)		
Tech Industry SES Class (ref = Low) Mid SES 1.17 (0.43) 1.24 (0.53) 1.17 (0.37) 1.08 (0.15) High SES 0.79 (-0.48) 0.92 (-0.15) 0.85 (-0.29) 0.86 (-0.24) Female 0.42** (-2.64) 0.42** (-2.61) 0.36** (-2.62) Race (ref = Low) Asian 1.85+ (1.65) 1.83 (1.61) 3.40** (2.68) Other 0.67 (-0.78) 0.76 (-0.52) 0.73 (-0.54) Cumulative GPA 1.08 (0.75) $\begin{array}{cccccccccccccccccccccccccccccccccccc$	Parent in Industry							0.74	(-0.90)
SES Class (ref = Low)         Mid SES       1.17       (0.43)       1.24       (0.53)       1.17       (0.37)       1.08       (0.15)         High SES       0.79       (-0.48)       0.92       (-0.15)       0.85       (-0.29)       0.86       (-0.24)         Female       0.42**       (-2.64)       0.42**       (-2.61)       0.36**       (-2.62)         Race (ref = Low)       1.85*       (1.65)       1.83       (1.61)       3.40**       (2.68)         Other       0.67       (-0.78)       0.76       (-0.52)       0.73       (-0.54)         Cumulative GPA       1.08       (0.75)       (0.75)       (4.42)         Parent in Industry       (-3.73)       0.42**       (-1.95)       0.26*       (-1.70)       0.27*       (-2.24)	Constant	$0.32^{***}$	(-3.73)	$0.47^{+}$	(-1.84)	$0.08^{***}$	(-3.41)	0.98	(-0.04)
Mid SES       1.17 $(0.43)$ 1.24 $(0.53)$ 1.17 $(0.37)$ 1.08 $(0.15)$ High SES       0.79 $(-0.48)$ 0.92 $(-0.15)$ 0.85 $(-0.29)$ 0.86 $(-0.24)$ Female $0.42^{**}$ $(-2.64)$ $0.42^{**}$ $(-2.61)$ $0.36^{**}$ $(-2.62)$ Race (ref = Low) $-0.67$ <td>Tech Industry</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>	Tech Industry								
High SES $0.79$ $(-0.48)$ $0.92$ $(-0.15)$ $0.85$ $(-0.29)$ $0.86$ $(-0.24)$ Female $0.42^{**}$ $(-2.64)$ $0.42^{**}$ $(-2.61)$ $0.36^{**}$ $(-2.62)$ Race (ref = Low) $-0.42^{**}$ $(-0.24)$ $0.42^{**}$ $(-2.61)$ $0.36^{**}$ $(-2.62)$ Asian $-0.67$ $(-0.78)$ $0.76$ $(-0.52)$ $0.73$ $(-0.54)$ Cumulative GPA $-0.67$ $-0.78$ $0.76$ $(-0.52)$ $0.73$ $(-0.54)$ Parent in Industry $-0.32^{***}$ $-0.373$ $0.42^{+}$ $(-1.95)$ $0.26^{+}$ $(-1.70)$ $0.27^{**}$ $(-2.24)$	SES Class (ref = Low)								
Female $0.42^{**}$ $(-2.64)$ $0.42^{**}$ $(-2.61)$ $0.36^{**}$ $(-2.62)$ Race (ref = Low)  Asian $1.85^{+}$ $(1.65)$ $1.83$ $(1.61)$ $3.40^{**}$ $(2.68)$ Other $0.67$ $(-0.78)$ $0.76$ $(-0.52)$ $0.73$ $(-0.54)$ Cumulative GPA $1.08$ $(0.75)$ Parent in Industry $0.32^{***}$ $0.32^{***}$ $0.42^{+}$ $0.42^{+}$ $0.42^{+}$ $0.26^{+}$ $0.26^{+}$ $0.26^{+}$ $0.26^{+}$ $0.27^{*}$ $0.27^{*}$ $0.27^{*}$ $0.27^{*}$ $0.27^{*}$ $0.27^{*}$ $0.27^{*}$ $0.28^{+}$	Mid SES	1.17	(0.43)	1.24	(0.53)	1.17	(0.37)	1.08	(0.15)
Race (ref = Low) Asian Other  Cumulative GPA Parent in Industry Constant $1.85^{+}$ $1$	High SES	0.79	(-0.48)	0.92	(-0.15)	0.85	(-0.29)	0.86	(-0.24)
Asian	Female			$0.42^{**}$	(-2.64)	$0.42^{**}$	(-2.61)	0.36**	(-2.62)
Other       0.67       (-0.78)       0.76       (-0.52)       0.73       (-0.54)         Cumulative GPA       1.08       (0.75)	Race (ref = $Low$ )								
Cumulative GPA Parent in Industry Constant  0.32*** (-3.73) 0.42+ (-1.95) 0.26+ (-1.70) 0.27* (-2.24)	Asian			$1.85^{+}$	(1.65)	1.83	(1.61)	3.40**	(2.68)
Parent in Industry Constant  0.32*** (-3.73) 0.42+ (-1.95) 0.26+ (-1.70) 0.27* (-2.24)				0.67	(-0.78)	0.76	(-0.52)	0.73	(-0.54)
Constant $0.32^{***}$ (-3.73) $0.42^{+}$ (-1.95) $0.26^{+}$ (-1.70) $0.27^{*}$ (-2.24)						1.08	(0.75)		
	Parent in Industry							6.41***	(4.42)
Observations 338 335 335 338			(-3.73)		(-1.95)		(-1.70)		(-2.24)
	Observations	338		335		335		338	

z statistics in parentheses

Observations include those who reported their post-graduate plans as employed or undecided.

 $<sup>^{+}</sup>$  p < 0.10,  $^{*}$  p < 0.05,  $^{**}$  p < 0.01,  $^{***}$  p < 0.001

Table 11: Odds Ratio of Employment by Industry

	Model 11		Mod	el 12	Model 13		
Other Industries							
Finance Industry							
SES Class (ref = Low SES)							
Mid SES	$2.70^{+}$	(1.67)	2.46	(1.50)	1.87	(0.96)	
High SES	$3.50^{+}$	(1.88)	2.95	(1.60)	1.99	(0.92)	
Female	0.56	(-1.57)	0.58	(-1.50)	0.61	(-1.21)	
Race (ref = White)							
Asian	1.69	(1.27)	1.44	(0.88)	2.06	(1.51)	
Other	0.40	(-1.34)	0.39	(-1.37)	0.48	(-0.98)	
Cumulative GPA					1.15	(0.99)	
Social Capital Index 1			1.62**	(2.62)	1.62*	(2.25)	
Social Capital Index 2			$0.67^{*}$	(-2.12)	0.74	(-1.43)	
Cultural Capital Index 1	1.29	(1.37)			1.33	(1.28)	
Cultural Capital Index 2	1.15	(0.78)			1.20	(0.95)	
Parent in Industry					1.04	(0.09)	
Constant	$0.14^{**}$	(-3.14)	0.16**	(-2.95)	$0.13^{+}$	(-1.90)	
Consulting Industry							
SES Class (ref. = Low SES)							
Mid SES	1.55	(1.13)	1.27	(0.60)	0.79	(-0.47)	
High SES	1.41	(0.74)	0.96	(-0.08)	0.50	(-1.17)	
Female	0.79	(-0.81)	0.88	(-0.45)	0.99	(-0.04)	
Race (ref. = White)							
Asian	1.33	(0.89)	1.22	(0.62)	1.51	(0.99)	
Other	$0.35^{*}$	(-2.18)	$0.37^{*}$	(-1.99)	0.76	(-0.46)	
Cumulative GPA					1.67***	(4.00)	
Social Capital Index 1			1.90***	(4.30)	2.16***	(4.01)	
Social Capital Index 2			0.88	(-0.90)	0.95	(-0.30)	
Cultural Capital Index 1	1.09	(0.61)			1.35	(1.58)	
Cultural Capital Index 2	$1.29^{+}$	(1.82)			1.60**	(2.69)	
Parent in Industry					0.55	(-1.55)	
Constant	$0.47^{+}$	(-1.82)	0.53	(-1.52)	$0.05^{**}$	(-3.14)	
Tech Industry							
SES Class (ref. = Low)							
Mid SES	1.25	(0.53)	1.15	(0.34)	0.82	(-0.38)	
High SES	0.86	(-0.27)	0.77	(-0.46)	0.51	(-0.93)	
Female	0.42*	(-2.55)	$0.43^{*}$	(-2.51)	$0.40^{*}$	(-2.26)	
Race (ref. = White)							
Asian	1.82	(1.54)	1.81	(1.57)	3.19*	(2.41)	
Other	0.59	(-1.01)	0.69	(-0.72)	1.01	(0.01)	
Cumulative GPA					1.31*	(1.97)	
Social Capital Index 1			$1.35^{+}$	(1.67)	1.25	(1.02)	
Social Capital Index 2			0.96	(-0.26)	1.06	(0.29)	
Cultural Capital Index 1	1.13	(0.70)			1.19	(0.81)	
Cultural Capital Index 2	1.45*	(2.22)			1.55*	(2.17)	
Parent in Industry		•			5.92***	(4.14)	
Constant	$0.42^{+}$	(-1393)	$0.46^{+}$	(-1.71)	0.06**	(-2.78)	
Observations	335	J1 ′	335		338	. ,	

z statistics in parentheses

Observations include those who reported their post-graduate plans as employed or undecided.

 $<sup>^{+}</sup>$  p < 0.10, \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

## 2.4 Human Capital

The findings in Model 9 around whether elite professions hire select more based on signals of merit than "other" industries. Those students who fall into a higher cumulative GPA category have a 1.32 times greater odds of working in consulting than "other" industries, with high statistical significance (p = 0.002). This model finds slightly positive and non-statistically significant comparisons for the role of GPA in the odds of working in finance (1.02 times higher, p > 0.10) and technology (1.08 times, p > 0.10) compared to other industries. Therefore, we find support for H2a only within the industry of consulting. When we account for cumulative grade point average, we also find that significant socioeconomic class difference only stand for the finance industry. High SES students have a 4.1 times higher odds of entering finance compared to low SES students (p < 0.05).

## Social Capital, Cultural Capital, and Transferred Human Capital

The findings in Model 12: Social Capital are consistent with H2b, which we hypothesized that social capital mediates achievement of employment in elite professional services (finance and consulting). The model also finds that social capital mediates achievement in the technology industry as well. Social Capital Index serves as a measure how much professional help a student had access to and actually leveraged in their search for an internship (see analytical strategy). Having a one unit higher social capital score in the first index held a 1.62 times higher odds of securing a job in finance (p = 0.009) than in "other" industries. The second social capital index interestingly indicated a 33 percent less likelihood (p < 0.05). Having a one unit higher social capital score held a 1.90 higher odds of securing employment in consulting (p = 0.001) than "other industries." Similarly, a one unit higher social capital score in the first index held a 1.90 times higher odds of securing a job in finance (p < 0.001) than in "other" industries. Having a one unit higher social capital score in the first index held a 1.334 higher odds of securing employment in consulting (p = 0.001) than "other industries. Finally, having a one unit increase of the first social capital index indicates a 1.35 times higher odds of working in technology (p < .10) than other industries. We therefore accept H2b and find that higher scores in certain types of social capital mediate outcomes in elite professional

services, with significance (p < 0.01). The second social capital index once again indicates a lower likelihood, 12.4 percent (p > .10) and 4.2 percent (p > .10), of working in consulting and technology, respectively, over "other" industries.

The findings in Model 11: Cultural Capital are partially consistent with H2c in that we find that cultural capital increases the likelihood of working in consulting over "other industries", but not in finance. More specifically, a one unit increase in Cultural Capital Index 2, which represents highbrow or "bougie" hobbies, increases a student's odds of working in consulting by 1.29 times, controlling for gender, race, and class. Within this sub-model, we find that cultural capital mediates the class difference in consulting. Meanwhile, this same cultural capital index measure has an insignificant effect on the likelihood of working in finance, and the statistically significant advantage of class for mid and high SES students still stands (p < 0.10). Additionally, this same cultural capital predictor indicates a 1.45 times higher odds of working in technology than in "other" industries (p < 0.05).

The findings in Model 10: Parent Capital are consistent with H2d for the finance and technology industry, but not consulting. We find that inherited parent human capital of a specific industry mediates the effect of class differences on achieving employment within that specific industry. We measured transferred parent capital using a dichotomous measure of matching parent background in which at least one parent matches the students' employment industry, in comparison to a student entering "other" industries but have at least one parent in technology, consulting, or finance. For example, a student working in finance who has at least one parent that either studied an MBA or worked in finance as well would qualify as a match. Having a parent with a matching background increased a student's odds of securing a job in technology over "other" industries the most significantly, by 6.407 times (p < 0.001). Parent human capital held a much smaller but still positive effect within finance, where it increased a student's odds of securing employment by 1.18 times (p > 0.10). Finally, within consulting, a matching parent background decreased the likelihood of the student entering consulting by 27 percent over "other industries" (p > .10).

## **Dominant Forms of Capital Within Each Elite Profession**

Finally, in Model 13: Combined, we are able to discern which forms of capital play the largest role in securing a employment within each elite industry over "other" industries. Within finance, the class effect is solely mediated with statistical significance by social capital index. Within the consulting industry, a combination of cumulative GPA, social capital, and cultural capital mediate the class difference.

Within finance, the class effect is mediated by social capital index 1, in which a one unit increase of social capital results in a 1.62 times higher likelihood (p = 0.025), controlling for all other forms of capital, gender, and race. The effect of class on finance employment over "other" employment is reduced to a 1.87 and 1.99 times higher odds without statistical significance (p > 0.10).

Within the consulting industry, a combination of cumulative GPA, social capital, and cultural capital mediates the class difference. A one tier increase in cumulative GPA results in a 1.67 times higher odds of employment in consulting over other industries (p < 0.001). Simultaneously, a one unit increase in social capital index 1 results in a 2.16 times higher odds (p < 0.001). Finally, a one unit increase in cultural capital index 2 results in a 1.60 times higher odds (p < 0.01). All three of these forms of capital hold extremely high statistical significance while simultaneously playing a sizable role in mediating the effect of class on working in consulting over other industries. We are left with a 20.7 percent and a 50.5 percent decreasing likelihood of entering consulting for mid and high SES students compared to low SES students.

Finally, within the technology industry, cumulative GPA, matching parent industry, and cultural capital mediate the effect of class. A one tier increase in cumulative GPA results in a 1.31 times higher odds of employment in consulting over other industries (p < 0.05). Simultaneously, having at least one parent in the technology industry increases students likelihood of entering technology by 5.92 times (p < 0.001). Finally, a one unit increase in cultural capital index 2 increases a student's odds by 1.55 times (p < 0.05). Notably, the race and gender control have large effects and statistical significance while all forms of capital are accounted for. Women are 61 percent less likely to enter technology over other industries (p < 0.05). Meanwhile, Asian-Americans have a 3.19 times higher

odds of entering technology (p = 0.016) over "other" industries compared to white students. Simultaneously, we once again find a 18.3 percent and a 48.6 percent decreasing likelihood of entering consulting for mid and high SES students compared to low SES students. If we run a logistic regression on whether SES class predicts technology jobs, controlling for race, we find that mid SES students are 2.38 times more likely to apply than low SES students (p < 0.01) and Asian-Americans are 1.71 times more likely to apply (p < 0.05). Therefore, we might hypothesize that the high percentage of Asian American parents in technology is driving this trend. Overall, the most impactful forms of capital in terms of effect size on technology employment outcomes are having a parent in the industry, followed by cultural capital, followed by cumulative GPA in that order (p < 0.05).

Overall, these findings reveal an interesting dynamic in which social capital highly mediates professional services industries (finance and consulting) employment outcomes. However, securing employment in the technology industry, which often touts itself as highly meritocratic, is most highly moderated by transferred parent capital. We hypothesize that this parent capital is in the form of human capital, but it could also be in the form of cultural capital. Within a field such as finance, students might assume that nepotism is at work due to the relative lack of technical questions and therefore higher importance of cultural fit. With the technology industry however, our exploratory analysis indicates that a parent in technology predicts interest in the industry, as measured by student applications to technology internships or jobs. Furthermore, systemic inequalities in secondary education and STEM abilities transfer through generations.

## **Conclusion**

Overall, this study found support that human capital (H2A) and social capital (H2B) mediate the positive effect of higher socioeconomic class on securing elite profession employment outcomes and highly selective employment. In order to do so, the data first confirmed H1, which hypothesized that class differences exist when controlling for gender and race. The first set of models shows that having higher human capital, as measured by grade point average, and social capital result in

significantly higher odds in securing selective employment. Within the second set of models, we find that within each industry a different form of capital becomes dominant and answered Research Question 1, which asked the question: which forms of capital play a larger role in securing employment in each industry compared to other non-elite employment? In finance, social capital solely has a significant mediating effect and even then, the effect of class is still positive though without significance. Meanwhile, within consulting, cumulative GPA, social capital, and cultural capital all increase a students odds of working in that industry over other non-elite profession industries. Finally, having a parent in the industry, cultural capital, followed by cumulative GPA in that order increased a student's odds of employment in the technology industry. The study finds support for the role of cultural capital (H2C) and transferred human capital (H2D) in mediating the effect of socioeconomic class on employment outcomes, but only within the consulting and technology industries, respectively.

These results have several limitations that should be addressed in future research. First, the completed survey sample covers 36 percent of the Dartmouth senior cohort in the class of 2019. However, the collected data shows significant racial and employment bias, with students entering consulting employment being over-represented and first generation students being underrepresented. Also having a small cohort meant that even though a high concentration of students fulfilled these employment outcomes, a different proportion of high SES students than mid SES students filling out this survey within an industry could also skew results. Second, the generalizability of this study is quite limited given how specific the symbols of capital are to the Dartmouth and elite professions ecosystems. Third, small cell sizes within certain populations prevented interaction effects between class and different forms of capital to be examined, which would be good future research.

Nonetheless, this study provides important evidence that low socioeconomic status students entering elite higher education institutions face barriers in achieving human capital, social capital, and other forms of capital that could even out their opportunities for elite employment. Elite employment in this project is defined as industries that pay six-figure salaries upon entry and that are accessible with just an undergraduate degree. Therefore, the opportunities for socioeconomic mo-

bility into the elite class, or the ten percent of the national income distribution, for students from low socioeconomoic backgrounds is slim even in elite higher education institutions. This study does not just reaffirms, but contributes to the existing literature by determining which forms of capital serve as mechanisms in reinforcing this commonly suspected phenomena in elite higher education.

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## Appendix A: Survey instrument

Note: The previous 2018 pilot study showed that people had averse reactions to be asking point-blank whether they had gone into finance or consulting. This led to the realization that the intentions of the survey should be less transparent so as to improve the user experience of the survey by decreasing feelings of judgment through what respondents perceive as narrow outlooks on their employment outcomes. Overall, even though the survey was a little longer than necessary, the response rate was much higher than the 2018 pilot survey, especially given the lower compensation. Survey testers who took the survey instrument reported back a median completion time of 10.5 minutes, which was then relayed to respondents within the recruitment e-mail.

## **Appendix B: Methods**

Selective Employment Qualitative Coding:

Firms listed below actually frequently appeared in the data sample, but are not inclusive of all options.

Consulting firms coded as highly selective (top 15/50 listed by prestige): McKinsey, Bain, BCG, Accenture, Deloitte, KPMG, EY, Oliver Wyman, L.E.K.

Common finance firms coded as highly selective (top 25/50 listed by prestige): Goldman Sachs, Morgan Stanley, J.P. Morgan, Bank of America Merrill Lynch, Deustche, Wells Fargo, Citigroup Other: Teach for America, U.S. Senate, Chevrolet, Ford

Graduate Schools: Harvard Law School, Stanford Law School, Geisel Medical School, Emory, University of Chicago Pritzker School of Medicine, Washington University in St. Louis, Columbia Premed Postbac, and UC Berkeley

Technology: Alphabet (Google), Facebook, Amazon, Apple, Microsoft Sources: (*Top Investment Banking Firms* N.d.) (*The Top 50 Consulting Firms In 2019 By Revenue, Prestige, Growth Employee Satisfaction* N.d.)

Principle Component Analysis Eigenvalues:

Table 12: Principle Component Analysis Dimensions: Social Capital Variables

	Eigenvalue	Variance Percent	Cumulative Variance Percent
Dimension 1	7.26	38.57	38.57
Dimension 2	4.72	25.07	63.65

Table 13: Principle Component Analysis Dimensions: Cultural Capital Variables

	Eigenvalue	Variance Percent.	Cumulative Variance Percent
Dimension 1	1.51	47.90	47.90
Dimension 2	0.61	19.35	67.26

## **Appendix C: Additional results**