Published in final edited form as:

Sci Educ. 2018 March ; 102(2): 283–303. doi:10.1002/sce.21330.

The conundrum of social class: Disparities in publishing among STEM students in undergraduate research programs at a Hispanic majority institution

Sara Grineski, Heather Daniels, Timothy Collins, Danielle X. Morales, Angela Frederick, and Marilyn Garcia

Department of Sociology & Anthropology, University of Texas at El Paso, El Paso, TX, USA

Abstract

Research on the science, technology, engineering, and math (STEM) student development pipeline has largely ignored social class and instead examined inequalities based on gender and race. We investigate the role of social class in undergraduate student research publications. Data come from a sample of 213 undergraduate research participants majoring in STEM at a Hispanic-majority institution. Based on generalized estimating equations that adjust for student demographics, research confidence, mentoring experiences, duration/number of research experiences, and clustering by major, we find that higher income students and continuing-generation students (vs. first-generation students) were significantly more likely to publish. Continuing-generation students had an even greater likelihood of publishing than first-generation students as students accrued more research confidence, spent more hours/week with faculty mentors, and conducted research for more months. Results suggest that undergraduate research programs designed to enhance diversity may help close some gaps (e.g., gender) but inadvertently reproduce class inequalities.

Keywords

first-generation college students; research productivity; social class; STEM; undergraduate research

1 | INTRODUCTION

Students have unequal opportunities and aspirations to pursue science, technology, engineering, and math (STEM) degrees and careers. The lack of diversity in STEM fields is problematic because society is being denied access to the creativity and brain power of large segments of the population. Better science is also generated when diverse groups of people work together (Freeman & Huang 2015). Researchers have documented gender disparities in

Correspondence: Sara Grineski, Department of Sociology & Anthropology, University of Texas at El Paso, University Ave., El Paso, TX 79968, USA. segineski@utep.edu.

ORCID

Sara Grineski, <http://orcid.org/0000-0002-3561-1755>

CONFLICT OF INTEREST

The authors have no conflicts of interest to declare.

STEM fields, as well as disparities by race/ethnicity. Undergraduate programs targeting STEM students have focused on reducing these inequalities.

Despite the substantial body of work exploring disparities in STEM degrees and careers by gender and race/ethnicity, social class disparities are often omitted in these analyses. Little is known regarding how social class might operate to advantage or disadvantage students along the STEM educational pipeline. The omission of social class in research on STEM students is notable, given that social class is found to be an important factor shaping outcomes in higher education more generally.

This study seeks to fill the gap in our understanding of how social class shapes the outcomes of college students in the STEM pipeline by reporting findings from a study of undergraduate students at a Hispanic-serving university who have participated in STEM-focused undergraduate research programs at this institution. Through a focus on the outcome of undergraduate publications, we seek to answer the question: Are undergraduate research programs that target STEM students minimizing or reproducing inequalities by social class? The goals of many undergraduate research programs are to keep socially disadvantaged students on the path to a graduate education and a scholarly career. Therefore, we examine undergraduate student authored research publications as the outcome measure of student success.

2 | LITERATURE REVIEW

2.1 | Inequalities in the STEM pipeline

The literature examining racial/ethnic and gender disparities in STEM fields is well developed (e.g., Legewie & DiPrete, 2014; Morgan & Mehta, 2004). Women have higher levels of educational attainment than men, but they pursue STEM degrees at much lower rates (Mau, 2016; Wang & Degol, 2016). It is also the case that White students obtain STEM degrees and enter STEM careers at higher rates than racial/ethnic minority students (Morgan & Mehta, 2004; Mwenda, 2010). Unlike race/ethnicity or gender, disparities by social class have rarely been explored. The case studies that have been conducted have focused on the importance of race when examining social class. When looking at high school students attending a 4-week summer science camp, low class students (i.e., those qualifying for financial aid) had less contact with mentors from similar backgrounds than did the other students, but the authors' analyses suggested that these class differences were due primarily to these students also being racial/ethnic minorities (Thiry, Weston, Laursen, & Hunter, 2012). While examining first-generation college student status among a group of 33 McNair Scholars, African American first-generation students were more similar to African American continuing-generation students than they were to White first generation in terms of their perceptions of research mentoring relationships (Ishyama, 2007). In a national study not focused on STEM majors, mother's educational attainment was a significant predictor of both White and African American students' educational aspirations, while parental income was not significantly related to aspirations in either group (Carter, 1999). Given the tight linkages between race and class in the United States, it can be difficult to disentangle the effect of class from race, especially in small-scale studies of one university.

In spite of the limited attention it has received, we believe that social class is a particularly important factor to consider, especially given the emergence of undergraduate programs designed to address diversity in STEM. Social class is found to be an important factor shaping college student outcomes. Family income and parental educational attainment constitute two important elements of social class in terms of college success. Coming from a low-income background has been linked with worse academic outcomes for students (Breckler, Teoh, & Role, 2011; Engle & Tinto, 2008; Hurtado & Ponjuan, 2005; Sirin, 2005; Stuber, 2011), especially for poor college students who attend economically depressed high schools and who retain close connections with their home communities (Jack, 2016). Students whose parents did not graduate from college (i.e., first-generation students) also have worse educational outcomes (Dennis, Phinney, & Chuateco, 2005; Lohfink & Paulsen, 2005; Pascarella, Pierson, Wolniak, & Terenzini, 2004). For example, first-generation college students in the United States have lower GPAs than their continuing-generation peers (Pascarella et al., 2004).

One way in which social class advantages are reproduced in higher education is through cultural capital (Winkler, 2010). Cultural capital, as introduced by Bourdieu (1986, 1994), involves having mastery over the cultural practices which a given social group recognizes as legitimate in a certain field; it includes social and technical knowledge, perceptions, and values (Abel, 2007). Cultural capital is field specific, meaning that what serves as cultural capital varies depending on what is powerful in a given context (Lareau, Evans, & Yee, 2016). In the university field, upper class students tend to command greater stocks of cultural capital than lower class students, since they have been raised in upper class families by college educated parents, and navigating college is almost second nature for them. Education systems are designed to respond to and reward this sort of cultural capital (Jaeger, 2011), which tends to be read as innate academic ability (e.g., wealthy students with high SAT scores are simply smarter than working-class students with average scores). The cultural capital advantages of wealthy students are often invisible to social elites such that the worse academic performance of working-class students, whose cultural capital does not align well with the university field, is seen to reflect innate deficiencies in academic ability (Bourdieu, 1986).

This perspective implies that first-generation college students would have smaller stocks of cultural capital relevant to the university field than continuing-generation students, and this assumption is supported by the literature on first-generation students. First-generation college students sometimes have trouble navigating the culture of academia (Ostrove & Long, 2007), since they are not familiar with middle-class norms and the “rules of the game” when it comes to college. First-generation college students often struggle to take advantage of college resources, seek help, capitalize on resume-building opportunities, such as internships, and participate in extracurricular experiences (Ostrove & Long, 2007; Pascarella et al., 2004). Additionally, first-generation college students are less likely to engage in research with faculty members as volunteers, for course credit, or for pay, when compared to their continuing-generation peers (Kim & Sax, 2009). This is not to say that first-generation students come to college with deficits only. They may have stocks of community cultural wealth, which can help them persist through college. Their community cultural wealth may include high aspirations despite difficult circumstances, a strong sense of commitment to

community well-being, abilities to access community resources, skills to maneuver through social institutions, and the capacity and desire to challenge inequality (Yosso, 2005).

2.2 | Undergraduate research programs

To retain diverse students in STEM, colleges and universities in the United States have implemented faculty-mentored undergraduate research programs. Many of these programs are funded by federal agencies and designed for undergraduate students from underrepresented groups majoring in STEM fields. Examples include the National Institutes of Health's RISE (Research Initiative for Science Enhancement), MARC (Minority Access to Research Careers) and BUILD (Building Infrastructure Leading to Diversity) programs, programs funded by the National Science Foundation, and programs funded by private foundations (e.g., Howard Hughes Medical Institute). Colleges and universities also operate their own internally funded faculty-mentored undergraduate research programs, designed to engage students, increase their persistence, and facilitate their admittance in graduate programs in STEM fields.

Students participating in such undergraduate research programs have experienced increases in self-confidence, active learning, and pursuit of science careers (Lopatto, 2007; Lopatto & Tobias, 2010), critical thinking and communication skills (Bauer & Bennett, 2003; Hunter, Laursen, & Seymour, 2007; Seymour, Hunter, Laursen, & DeAntoni, 2004), and performance as graduate students (Gilmore, Vieyra, Timmerman, Feldon, & Maher, 2015). However, the complex roles of class, gender, and race in shaping gains among student participants have not been adequately disentangled. Specific to summer research programs, men participants reported fewer gains in their learning than women (Lopatto, 2007), but women and men were similar in their plans to continue their education (Lopatto, 2004). Across different programs at one university, men and women had similar self-assessed gains from undergraduate research participation (Daniels et al., 2016). There is a small body of evidence showing that racial/ethnic minority students gain more from undergraduate research programs than their white peers (Daniels et al., 2016; Jones, Barlow, & Villarejo, 2010; Lopatto, 2007; Russell, Hancock, & McCullough, 2007). But a few studies find the opposite (Lopatto, 2004); at one Hispanic serving institution, undergraduate research participation was less beneficial to Hispanic students as compared to White students (Collins et al., 2017). While social class is an important influence on college education outcomes (Bozick, 2007; Paterson & Iannelli, 2007; Reise, 2011), it is currently unknown whether social class shapes student outcomes (e.g., research publications) within STEM-focused undergraduate research programs. Undergraduate research outcomes for students from lower class backgrounds (e.g., those whose parents did not attend college), for example, have rarely been compared to those whose parents attended college (e.g., continuing-generation students), even though they are an important group to enable via targeted interventions (Engle, Bermeo, & O'Brien, 2006; Inkelas, Daver, Vogt, & Leonard, 2007; Stephens, Hamedni, & Destin, 2014).

2.3 | Academic research publishing

Scholarly publishing is an expectation in academic and research careers in STEM fields. Budding STEM scholars are quickly inculcated into the "publish or perish" culture of

academe for legitimate reasons, as publishing early in scientists' careers powerfully predicts their future success (Horta & Santos 2016; Laurance, Useche, Laurance, & Bradshaw, 2013; Swihart, Sundaram, Höök, & Dewoody, 2016; Van Dijk, Manor, & Carey, 2014). As early as their undergraduate years, students become aware of the importance of publishing to gaining acceptance into competitive graduate programs (Davis & Warfield, 2011). Students who have published report growth in critical thinking, logical thinking, analytic thinking, and scientific thinking (Lei & Chuang, 2009). Notably, there are no published studies examining correlates of undergraduate STEM students publishing their research, despite its important influence on their future careers.

Scholars' demographic characteristics and work habits have been shown to influence their productivity. Drawing from the literature on faculty and graduate student publishing (given the absence of research on undergraduates), we have identified the following salient influences on publishing: confidence in one's ability to do research (i.e., research self-efficacy; Forester, Kahn, & Hesson-McInnis, 2004; Kahn, 2001; Psaupathy & Sitwatu, 2014), amount of time spent on research activities (Ito & Brotheridge, 2007), duration of career (Swihart et al., 2016), age (Horta & Santos 2016), race (Eagan & Garvey, 2015), and gender (Bird, 2011; Eagan & Garvey, 2015; Horta & Santos, 2016; Laurance et al., 2013; Schuster & Finkelstein, 2006; Swihart et al., 2016). Having more confidence in one's ability to do research is a strong predictor of graduate student publications (Kahn, 2001). Not surprisingly, faculty who report spending more time on research activities (Ito & Brotheridge, 2007) and who have longer careers (Swihart et al., 2016) have higher numbers of publications, although yearly productivity does decline with age (Horta & Santos, 2016). Among undergraduate students, however, it stands to reason that older age would be positively related to publishing, given that mature students often perform better academically than traditionally aged students (Heagney & Benson, 2017; Richardson, 1994; Richardson & King, 1998). Racial/ethnic minority faculty publish less than White faculty members; a study examining a national (U.S.) sample of full-time undergraduate faculty at 4-year institutions revealed that faculty of color produce significantly less published research than their White colleagues (Eagan & Garvey, 2015). Regarding faculty gender, men publish almost twice as much as women, but this gap narrows when accounting for the varying publication rates across the academic disciplines (Schuster & Finkelstein, 2006).

In addition, faculty mentors are likely important since they are critical in helping undergraduate STEM students understand the importance of publishing (Schwartz, 2012a) and in shaping realistic expectations of the publishing experience (Pacifi & Thomson, 2011). Socially disadvantaged undergraduate research program participants have described their faculty mentors as a "door openers," in the sense that they offer research opportunities and deep knowledge of academic publishing, graduate school, and academic/science culture (Schwartz, 2012a). These findings underscore the importance of spending time face-to-face with their faculty mentor and having conversations about publishing research.

Prior studies outline factors that influence the likelihood of publishing, yet they do not speak to the role of social class. Consequently, we do not know if undergraduate research programs are reproducing social class-based inequalities in STEM fields or if they are facilitating closure of gaps between students from socially disadvantaged versus advantaged

backgrounds. We hypothesize that we will find a social class gaps in publishing among undergraduate research participants because (1) the literature shows disparities in publishing based on disadvantaged social status (in terms of race/ethnicity and gender) and (2) publishing research likely requires a specific form of cultural capital that lower class undergraduate students may not yet have acquired. We address this gap by examining two dimensions of social class (income and first-generation student status) as predictors of undergraduate research productivity.

2.4 | Conceptual model

We employed the input–environment–output (IEO) model to orient the study (Astin & Antonio, 2012). The purpose of the IEO model is to inform multivariate analyses that control for the effects of differences in initial student attributes and in student exposure to educational environments while in college, to minimize the chances of arriving at invalid inferences regarding the influence of particular educational interventions on student developmental outcomes. In other words, the aim is to adjust for potentially biasing variables to accomplish by statistical means what random assignment enables in controlled experiments. Inputs are independent variables that denote attributes that students bring initially into the institution’s educational programs. Environment variables measure students’ experiences during their time at the institution that influence student development (Astin & Antonio, 2012).

Figure 1 presents an IEO model that incorporates variables likely to influence publications among undergraduate research program participants, based on the literature review (see Figure 1). Specifically, we examined student sociodemographic characteristics (social class, ethnicity, sex, and age), scholarly gains in the form of research confidence, mentoring experiences, and the duration/number of research experiences to predict the odds of academic publishing.

After examining the main effects, we tested to see if one’s social class background modified the associations between the environment and publishing. This allowed us to examine if one’s social class background intensifies or attenuates the impacts of the environment on the likelihood of publishing. We hypothesize that being of low social class will attenuate positive associations between scholarly gains, mentoring experiences, duration/number of research experiences, and the likelihood of publishing.

3 | DATA AND VARIABLES

3.1 | The place

This study takes place at a Hispanic-serving institution (HSI). This is relevant because HSIs are an important entry point for students from working-class backgrounds (Finley & McNair, 2013) and for Latinos/as (Crisp, Nora, & Taggart, 2009) in STEM fields. This study examines factors influencing students’ odds of publishing their research, among a sample of undergraduate research participants from ten different programs at the University of Texas at El Paso (UTEP). UTEP is regarded as being supportive of student engagement (Kuh, Kinzie, Schuh, & Whitt, 2010) and provides an illustrative context to examine publishing outcomes

between socially disadvantaged and advantaged students. Institutional records indicate that 65% of senior undergraduates at UTEP from 2008 to 2012 were first-generation college students, meaning that neither parent had earned a BA degree and 39% had neither parent earning more than a high school diploma; 76% were in need of financial aid (i.e., from lower income families) (University of Texas at El Paso, 2014). Additionally, the student body at UTEP is majority Hispanic; over 80% of the 20,000 undergraduates are Hispanic/Latino. These unique demographics make it possible to examine variations in social class within a predominately Hispanic population.

3.2 | Data collection

The survey used was based primarily on the Undergraduate Research Student Self-Assessment (URSSA) and the College Student Report included in the National Survey of Student Engagement (NSSE). It was Institutional Review Board approved (UTEP IRB No: 503441-1) and administered to participants using Qualtrics Survey Software. The URSSA was originally designed to capture important student outcomes of undergraduate research experiences. The URSSA instrument has been well-tested, and the reliability and validity of the items have been repeatedly verified (e.g., Weston & Laursen, 2015). The College Student Report instrument examines college students' engagement in institutionally based programs and activities designed to enhance their learning and development. The survey items can be used to procure reliable and valid estimates of how college students spend their time and what they gain from attending college (NSSE, 2015).

The survey was sent to students currently enrolled in undergraduate research programs (the end of the Fall 2013 semester) and to students who participated in an undergraduate research program within the past 5 years (2009–2013), including recent graduates. All students in the sampling frame ($n=408$) had participated in their undergraduate research program ($n = 10$ different programs at UTEP) for at least one semester or one summer, although some students had been in their program for several years. These 10 programs included BRIDGES (Bridges to the Baccalaureate Program), COURI (Campus Office for Undergraduate Research Initiatives), LSAMP (Louis Stokes Alliance for Minority Participation), MARC (Minority Access to Research Careers), the Provost's Office Summer Research Assistant program, RISE (Research Initiatives for Scientific Enhancement), SMARTMIND (Summer Mentoring and Research Training program in Methods in the Neuroscience of Drug-addiction), SMARTS (Student Mentoring to Achieve Retention: Triads in Science), STEM-RTI (STEM Research Teaching Integration), and UPBIT (Undergraduate Participation in Bioinformatics Training).

The survey was active for 4 weeks (beginning in the middle of November 2013 and ending in the middle of December 2013). To bolster response rates, we sent a prenotification email, three email reminders to nonrespondents (Manfreda & Vehovar, 2008), and two waves of postcards to the students' permanent addresses. Students were provided a \$10 gift card as an incentive. A total of 227 students completed the survey making the response rate 53%. We analyzed data from 213 students after removing five due to their non-STEM majors (e.g., commercial music, marketing) and nine due to missingness of more than 60% of responses for the analysis variables.

4 | VARIABLES

4.1 | Output variable

The dependent variable is a dichotomous indicator of whether or not the STEM student reported having a research paper in the peer review process or already published. This measure, drawn from the URSSA, was related to students' most recent undergraduate research program experience. Specifically, students were asked to indicate either yes/no if they had either: written/cowritten a paper that is currently under review with an academic journal or written/cowritten a paper that was published in an academic journal. These answers were combined to create the dependent variable. Students who indicated having both were counted the same as students who indicated only having one of the two. Ideally, we would have examined only students with a paper already published, but given the low count, we expanded to include those with papers in review. In the sample, 24.9% reported having a paper published or in the peer-review process. We did not include students who indicated that they were planning to submit a paper for review with an academic journal. Table 1 includes descriptive statistics of the dependent variable and the independent variables as well. Table 2 provides cell sizes for the dichotomous variables based on the published outcome variable.

4.2 | Input variables

We used four separate input measures, which were sociodemographic variables. To conceptualize class, we use two variables. *Income* was measured on a 9-point scale ranging from 1 (under \$10,000 per year) to 9 (over \$250,000 per year) and a *first-generation college* student variable was created by reviewing each parent's highest level of education. Students indicating neither parent attained a bachelor's degree or higher were recoded as 1, to indicate first-generation college student status. If the student had only one parent, the education-level of that single parent was used to determine first-generation status. This follows one of the two recommendations for coding first-generation college student status according to the NSSE. The second recommendation is to define first-generation status based on the parents having no college experience (e.g., a high school diploma or less), and so we conducted a sensitivity analysis whereby we defined first-generation student status that way instead. *Age* was calculated by subtracting the student-reported birth year from 2013, being that this is when the survey was administered. *Sex* was demarcated with 1 for male and 0 for female. Being *Latina/o* or Hispanic was coded as 1 for yes and 0 for no.

In terms of the how the sample of STEM majors compares to the UTEP student body on the inputs, approximately 50% of respondents were first-generation college students, defined based on neither parent attaining a bachelor's degree; 25% had neither parent having any college experience. By both definitions, first-generation students are underrepresented in undergraduate research programs at UTEP; by comparison, 65% of UTEP seniors do not have parents who have earned a BA and 39% have parents with no college experience. In the sample, 58% of participating students were women; this suggests that women are overrepresented in undergraduate research programs at UTEP, since 52% of full-time undergraduate students at UTEP are women (University of Texas at El Paso, 2014). Eighty-nine percent of respondents identified themselves as Latino/a, which is a very close match to

the campus wide statistics: Eighty-two percent of UTEP undergraduates are Latino/a/Hispanic, and approximately 9% are Mexican international students (University of Texas at El Paso, 2014).

4.3 | Environment variables

The environmental variables are related to the student's most recent undergraduate research program experience. In terms of scholarly gains due to the undergraduate research experience, we created a *gained research confidence* factor, which is similar to measures that have been used in previous studies (e.g., Kahn, 2001; Psaupathy & Sitwatu, 2014). Each of three items on the survey instrument were rated on a five-point Likert scale ranging from 1 = no gain to 5 = a great gain and related to students' most recent research experience. The first item asked students to rate their gains in their abilities to formulate a research question answerable with data. The second asked students to assess their gains in confidence in their ability to contribute to science. The third asked students to rate their gains in using conventional techniques, methods, and technologies to conduct research in their field. We used principal components analysis to create the factor and the Cronbach's alpha score was .851, indicating that the factor is reliable. We used only the first extracted factor, as it explained 72.5% of the variance with an eigenvalue of 2.175. The second and third factors had eigenvalues under 1 and explained only 17.4% and 10% of the variance, respectively.

Two variables were used to operationalize the students' mentoring experiences that took place through their undergraduate research training. The *time with mentor* variable (from URSSA) was measured on a 4-point scale ranging from 1 (1 hour per week or less) to 4 (4 or more hours per week). *Having regular face-to-face meetings with a mentor* is a dichotomous indicator taken from a checklist of program resources provided to the student, which we designed based on each program's offerings.

We also considered research experiences, specifically the duration and number of research experiences. The *months in research* variable was constructed by converting the reported numbers of summers and semesters spent doing research into a sum of total months. The *participation in multiple programs* was created by coding a student 0 if he/she had participated in just one program and 1 if he/she had been in 2 or more programs, based on a checklist of the possible programs.

For descriptive purposes, we present Pearson's correlation coefficients between analysis variables (table not shown); * is indicative of $p < .05$ and ' of $p < .10$. Students who had published were older (corr. = .192*), had spent more months doing research (corr. = .221*), were more likely to have regularly scheduled meetings with their mentors (corr. = .117'), and had higher incomes (corr. = .138'). First-generation students were older (corr. = .160*), had spent more months doing research (corr. = .188*), and had spent more hours per week with their mentors (corr. = .125'). Students with higher incomes had spent fewer months in research (corr. = -.154*) and were less likely to do more than one program (corr. = -.125'). Older students spent more hours/week with their mentors (corr. = .186*), were less likely to be Latino/a (corr. = -.220'), and had spent more months in research (corr. = .189*). Greater research confidence was associated with more hours/week with the mentor (corr. = .300*), regularly scheduled meetings with the mentor (corr. = .244*), and more months in research

(corr. = .134'). Spending more hours/week with the mentor was associated with having regularly scheduled meetings with the mentor (corr. = .134'). Students who had done more months of research were more likely to have participated in more than 1 program (corr. = .295*).

4.4 | Analysis strategy

We began the analysis by addressing the issue of missing data. We used multiple imputation (MI) to address the bias that occurs when missing data points are not missing completely at random (MCAR) (Penn, 2007). MI uses a regression-based approach to create multiple sets of observations for missing values and is commonly used for self-reported survey data (Enders, 2010). We used MI to impute the missing data points for all analysis variables before modeling the generalized estimating equation or GEE. We specified imputed data sets to maximize power and improve the validity of multiparameter significance tests. We used 200 between-imputation iterations to ensure the imputed data sets were independent (Enders, 2010). The MI process adjusts the standard errors as part of the pooling process (Enders, 2010), wherein separate results for each data set are combined into one set of pooled results, which we report here. The percent missing for each variable is included in Table 1. As is recommended practice in MI, the ordinal independent variables (e.g., income), were standardized after MI and analyzed as continuous predictors. This is recommended because rounding off imputed values to align with categorical specifications results in more biased parameter estimates (Allison, 2005; Enders, 2010; Horton, Lipsitz, & Parzen, 2003; Rodwell, Lee, Romaniuk, & Carlin, 2014). MI data were used in the multivariate GEE model, whereas original data were used in the univariate analysis (i.e., descriptive statistics presented in Tables 1 and 2).

GEEs with robust (i.e., Huber/White) covariance estimates extend the generalized linear model of Nelder and Wedderburn (1972) to accommodate clustered data and are used here. They provide a general method for the analyses of clustered variables and relax several assumptions of traditional regression models (Diggle, Liang, & Zeger, 1994; Liang & Zeger, 1986; Zeger & Liang, 1986). GEEs imply no strict distribution assumptions for independent variables and are appropriate for use with nonnormally distributed dependent variables. Clusters of observations must be defined to fit a GEE model. It is assumed that observations from within a cluster are correlated, whereas observations from different clusters are independent. In the GEEs used, students were clustered into four different STEM major groupings: physical and life sciences (e.g., biology, chemistry, biochemistry, physics, and mathematics) ($n = 88$), engineering (e.g., mechanical, electrical, metallurgical, and materials) ($n = 26$), social and behavioral sciences (e.g., sociology, psychology) ($n = 5$), and health sciences (e.g., kinesiology, clinical lab sciences) ($n = 8$); 86 students were missing data for major. We control for major clustering as a nuisance parameter in the model because there are different rates of undergraduate participation by major at UTEP (Collins et al., 2017) and different rates of publication by academic field (Baily, 1992; Horta & Santos, 2016; Quimbo & Sulabo, 2014).

GEEs also require the specification of an intracluster dependency correlation matrix (Liang & Zeger, 1986; Zeger & Liang, 1986). While other statistical techniques may account for the

intraclass correlation, especially when the dependent variable is normally distributed, GEEs offers the additional advantage of not requiring the correct specification of the correlation matrix to reach unbiased statistical conclusions about the covariates' effects, given that the robust estimation of standard errors be applied (as is the case in our analysis). In this case, we specified the exchangeable correlation matrix, which assumes constant intraclass dependency (i.e., compound symmetry), so that all the off-diagonal elements of the correlation matrix are equal (Garson, 2012), which was done in a related study (Daniels et al., 2016).

For our purposes, GEEs are preferable to other modeling approaches that account for nonindependence of data (e.g., mixed models with random effects). This is because GEEs estimate unbiased population-averaged (i.e., marginal) regression coefficients, even with misspecification of the correlation structure when using a robust variance estimator (Liang & Zeger, 1986; Zeger & Liang, 1986). Additionally and more importantly, because our focus is on predicting student publishing at the individual level, and not multilevel effects of student major on publishing, GEEs are appropriate because the intraclass correlation estimates are adjusted for as nuisance parameters and not modeled (as in multilevel modeling approaches) (Diez Roux, 2002).

Based on the dependent variable being dichotomous, we used a binomial distribution to model our dependent variable. To find the best fitting model, we fit GEE models predicting our dependent variable trying five different link function specifications: complementary log–log link, log link, logit link, negative log–log link, and probit link. We selected the negative log–log link function for the final GEE model because this specification yielded the lowest quasi-likelihood under independence criterion (QIC) scores. The “negative log–log” option assumes that the estimated probability is asymmetric with respect to the predictor, with lower values of the dependent being more probable (Garson, 2012), which was the case with our dependent variable. While the QIC allows the analyst to select the best fitting model, it does not indicate the proportion of variance explained.

We estimated seven models. First, we predicted publishing using the input (sociodemographic variables) and environmental variables (scholarly gains, mentoring experiences, and duration/number of research experiences). Then, we interacted first-generation college student status with each of the sets of “environment” variables. Our second model includes the main effects and the interactions between the first-generation status variable and gained research confidence. The third model shows main effects and interactions between first-generation status and mentoring experiences. The fourth model lists main effects and the interactions between first-generation status and the two research experience variables. We did not include all interaction terms in the same model due to our sample size and concerns about statistical power. Then, we ran the three interaction models again, using income in place of first-generation student status. Based on variance inflation factor, tolerance, and condition index criteria, inferences from the GEEs are not affected by multicollinearity. As a sensitivity analysis, we replicated these same analysis steps using a second definition of first-generation student status whereby the parents had no college experience, instead of the definition based on the parents not earning a BA degree. As a

second sensitivity analysis, we replicated the models, controlling for clustering by research program instead of by major grouping.

5 | RESULTS

Results of the GEE for the main effects model are listed in Table 3 (column A). In terms of the sociodemographic inputs, students who had a higher income were significantly ($B = .202, p < .05$) more likely to have a paper under review and/or published. First-generation college students (i.e., the parents were without college degrees) were significantly ($B = -.327, p < .05$) less likely to have a paper under review and/or published than were continuing-generation students. Older age was positively related to having a paper under review and/or published, but the finding was not significant ($B = .209, p < .10$). Being male or Latino/a did not significantly predict having a paper under review and/or published. In terms of the environment variables, gained research confidence was not significantly associated with having a paper under review and/or published. As for the mentoring experiences variables, having regularly scheduled face-to-face meetings with the mentor was significant ($B = .337, p < .05$) and positively associated with having a paper under review and/or published, while time with mentor was not significant. Regarding the research experience variables, students who reported spending more months doing research were more likely to have a paper under review and/or published, but the finding was not significant ($B = .297, p < .10$). Engagement in more than one program was not significantly associated with having a paper under review and/or published.

The results of interactions between first-generation college students and the gained research confidence variable ($p < .05$) are presented in Table 3 (column B) and graphed in Figure 2. As gained research confidence increases, continuing-generation students are more likely to publish; for first-generation students, the slope is slightly negative, suggesting that they are even less likely to publish as their gained research confidence rises. Income, first-generation, and regularly scheduled face-to-face meetings remained significant ($p < .05$) and age, months in research, and the gained research confidence term became significant and positive ($p < .05$). The confidence finding suggests an overall positive association between gained research confidence and publishing, although the interaction term reveals that it is significantly stronger for continuing-generation students.

The results of interactions between first-generation college students and mentoring experiences are described in Table 3 (column C) and graphed in Figure 2. As the student spends more time with his/her mentor, continuing-generation students are more likely to publish; for first-generation students, the slope is actually negative, suggesting that they were even less likely to publish if they spent more time with their mentors. In terms of main effects, income, face-to-face meetings, and age, were significant ($p < .05$). The direct effect of first-generation remains negative but drops in significance.

Interactions between first-generation status and duration/number of research experiences ($p < .05$) are shown in Table 3 (column D) and graphed in Figure 2. As both first- and continuing-generation students spend more months doing research, they are more likely to publish, but the relationship is stronger for continuing-generation students. In terms of direct

effects, income, first generation, age, face to face, and months in research were positive and significant ($p < .05$). None of the interactions with income were statistically significant, and so those models are not shown in a table.

In terms of the first sensitivity analysis exchanging the first-generation (no college degree) variable for the first-generation (no college experience) variable, the results were generally in agreement in terms of directionality with some shifts in significance from $p < .05$ to $p < .10$ and vice versa. All findings that were significant in the main effects model shown in Table 3 (column A) were also significant when using the second definition of first-generation student; age and months in research were also significant ($p < .05$) and positive. In terms of the interactions, the interaction with confidence and with time with mentor remained significant ($p < .05$), but the interaction with time in program lost significance ($p > .10$).

In the second sensitivity analysis, we ran the models controlling for clustering by program (i.e., we used each program plus a category for more than one program). The key findings were the same in direction and significance (i.e., income, first generation, and regular meetings were still significant at $p < .05$ in the main effects model). Two of the three interaction findings decreased in significance: “first-gen. X regular meetings” dropped to $p = .06$ and “first-gen. X months in research” dropped to $p = 0.146$, whereas “first-gen. X confidence” stayed significant at $p < .001$. We do not feature these (or other program-specific) results more prominently in the paper due to confidentiality concerns of the program directors who shared their participant lists with us, some of whom specifically asked that we not compare programs to each other.

6 | DISCUSSION

Previous research has left open the question as to whether undergraduate research programs are reproducing social inequalities along the STEM educational pipeline by further enabling more socially advantaged students to achieve more successful outcomes or closing the gaps between disadvantaged and advantaged students as is the ultimate goal of most undergraduate research initiatives. Our results suggest that undergraduate research programs at this Hispanic-majority institution are reinforcing some gaps (e.g., social class) while closing others (e.g., gender) in terms of the likelihood of students publishing.

The findings for first-generation students and low-income students suggest that students from low social class backgrounds face disadvantages with regard to publication outcomes and that undergraduate research opportunities may not do enough to level the playing field for these students. Even in terms of the basic descriptive statistics, first-generation students are underrepresented as undergraduate research participants as compared to the composition of the UTEP undergraduate student body. The significance of these two social class variables in the presence of one another suggests that family economic circumstances and parental educational attainment have distinct influences on student outcomes. We found that undergraduate research program participants who were first-generation college students were less likely to have a paper under review and/or published compared to students who were not. This is in line with studies which have shown other educational disadvantages for

this group (Carter, 1999; Dennis et al., 2005; Lohfink & Paulsen, 2005; Pascarella et al., 2004). Compared to students with highly educated parents, first-generation students may be less aware of how to “play the game” in the context of research and of the importance of publishing their research; in other words, they may not yet have the cultural capital needed in the academic playing field. Pascarella et al. (2004) made a similar argument with respect to educational aspirations. First-generation students, as they persisted through college, planned to obtain lower level degrees, as compared to their continuing-generation peers, which suggests that continuing-generation students may have higher educational attainment expectations and/or be more aware of the importance of advanced degrees within the labor-market compared to first-generation college students (Pascarella et al., 2004).

The interaction findings suggest that having first generation status is associated with less effective acquisition and deployment of cultural capital throughout the research process based on the lower likelihood of publishing. Interaction findings show that continuing-generation students have enhanced odds of publishing when they spend more time with the mentors, when they have greater gained research confidence, and when they have longer duration research experiences, as compared to their first-generation peers. Personal contact between mentors and mentees enables communication, increases student learning, and provides adequate time for mentors to transmit the values and norms of academic publishing (Pacifi & Thomson, 2011; Schwartz, 2012a). It is interesting however that this time was beneficial to continuing-generation students in a way that it was not for first-generation students. Being unable to ask the ‘right’ questions and feeling uncomfortable asking for help within these regular interactions due to cultural capital mismatches between the students and their mentors may hinder first-generation college students and impede their progress within their research experiences, even when they spend sufficient time with their mentors. While not a perfect comparison, it is interesting that another study found that racial/ethnic minority students were less likely to persist in a STEM major when they had more faculty mentoring (defined based on support, guidance, research opportunities, letters of recommendation, help to achieve goals, and encouragement to attend grad school) (Chang, Sharkness, Hurtado, & Newman, 2014); this also suggests that time with faculty is not universally beneficial for all student types.

Furthermore, higher gained research confidence was more beneficial for continuing-generation students. Research confidence was not significant in the main effects model, but it became significant in the model including the interaction of first-generation status with confidence, which was also significant. This suggests that while enhanced research confidence has a generally positive effect on publishing, the effect is significantly stronger for continuing-generation students. These results imply that while confidence is relevant to predicting graduate- and faculty-level productivity (Kahn, 2001; Psapathy & Sitwatu, 2014), at the undergraduate level it is most relevant to continuing-generation college students’ productivity. Even as first-generation students grow in their confidence to conduct research, it does not translate into increased odds of publishing, as it does for continuing-generation students. First-generation and continuing-generation students do not have significantly different research confidence scores ($p = .56$, table not shown), suggesting that it is not the case that continuing-generation students are gaining more confidence than first-

generation students, but instead that first-generation students are unable to translate that gained confidence into a publication.

Longer duration research experiences were also more beneficial to continuing-generation students in terms of increasing their odds of publishing. Other studies have highlighted the importance of longer duration undergraduate research programs to increase the benefits of participation (Adedokun et al., 2014; Daniels et al., 2016; Thiry, Weston, Laursen, & Hunter, 2012) and noted that spending more time on research is linked to more publications (Ito & Brotheridge, 2007). While the direct effect was positive in the main effects model ($p < .10$), the interaction findings revealed that longer duration research experiences were not as beneficial for first-generation students' odds of publishing as they were for continuing-generation students. While longer duration implies more time to conduct research and write up results in an absolute sense, students who spend more months doing research also have more time to immerse themselves in interactive research environments. However, the interaction finding suggests that first-generation students are less able to extract these benefits from additional months doing research in the same manner as the continuing-generation students.

Even when accounting for first-generation student status, undergraduate researchers from lower income backgrounds faced a publication disadvantage. Although UTEP has been regarded as a highly supportive context in terms of student engagement (Kuh et al., 2010), the findings here for undergraduate publications seem to reflect a broader pattern whereby there are poorer educational outcomes for students from low-income backgrounds compared to their wealthier peers (Engle & Tinto, 2008; Stuber, 2011). Higher income often means more access to resources, and in the context of undergraduate research it may mean not having to work off campus and therefore having flexibility in one's schedule to attend meetings, work on experiments at odd hours, and generally be more available to one's research mentor and team. Additionally, interaction results revealed that the influence of higher income on publication was not modified by any of the other variables, meaning that higher incomes might be similarly beneficial for everyone. This suggests the possibility that income does not reflect distinctions in cultural capital in the same way that first-generation student status does. When looking specifically at gains from undergraduate research, an analysis of the same students revealed that income was not significantly related to self-assessed growth in research skills or science identity, although higher income students reported slightly greater gains (Daniels et al., 2016). This indicates that while students with lower incomes may not feel like they have learned less from their research programs than their higher income peers, they do publish less.

We found that men and women had statistically similar odds of publishing. This finding is notable, given the numerous studies showing that men publish more than women faculty (Bird, 2011; Horta & Santos, 2016; Eagan & Garvey, 2015; Laurance et al., 2013; Schuster & Finkelstein, 2006; Swihart et al., 2016). At this early precareer stage, the lack of a male advantage may reflect the higher levels of success in general for women versus men college students (Cole & Espinoza, 2008; Conger & Long, 2010; DeBerard, Spielmans, & Julka, 2004; DiPrete & Buchmann, 2013). An optimistic reading of the finding is that it could signal a generational shift with regard to publishing among future women faculty, since early

career publication is an important factor in predicting later career success (Horta & Santos, 2016; Laurance et al., 2013; Swihart et al., 2016; Van Dijk et al., 2014). Women were also overrepresented in this sample of undergraduate research participants, suggesting that they are not being excluded from participating at the point of entry. When paired with the gender equality finding for publishing, these results suggest that women are not at a distinct disadvantage in this context.

While race/ethnicity has been examined less often than gender, minority faculty have been shown to publish less (Eagan & Garvey, 2015). We found no significant publishing differential for Latino/a versus non-Latino/a undergraduate research students. The Hispanic-majority context of UTEP is important to recognize since approximately 80% students at UTEP and in this sample are Hispanic. It is not clear if the ethnicity finding would be similar at a non-Hispanic majority institution, but future research should examine that. We had only 23 non-Hispanic participants in the study, which may have increased the standard errors and limited the possibility of a statistically significant finding. These students were also from a mix of racial backgrounds, including African American, Asian, and non-Hispanic White, which prevented any comparisons of students from particular non-Hispanic racial/ethnic backgrounds with Hispanic students. The number of undergraduate student researchers from other racial/ethnic backgrounds in our sample was simply too small to enable such comparisons here, but future studies should seek to conduct more nuanced analyses of the role of race/ethnicity and social class in undergraduate publishing. Older age was also associated with greater odds of publishing. Among faculty, yearly productivity decreases with age (Horta & Santos, 2016), but among this younger cohort of undergraduate students, older age is likely associated with greater maturity and more academic skill (Hoskins, Newstead, Dennis, 1997; Halpern 2007) and thus greater odds of publication.

Students who have regularly scheduled meetings with their mentors were more likely to publish than those who did not. The interaction effect was not significant meaning that students who have regularly scheduled meetings with their mentor are more likely to publish whether they are first-generation or not. Regular meetings are important for good mentee–mentor communication (Girves, Zepeda, & Gwathmey, 2005). It is also probable that the accountability structure created through regular meetings helps bolster productivity.

6.1 Limitations and future directions

To date, no existing studies have examined the correlates of undergraduate students publishing their research findings. This is an important gap in the literature given the critical importance of publications for graduate school admissions (Davis & Warfield, 2011) and the myriad efforts currently underway to promote the persistence of socially disadvantaged students in STEM fields, such as those efforts by the U.S. National Institutes of Health's RISE, MARC, and BUILD programs. This means that none of our results have been found previously in other studies on the same topic. We do not know if any of the findings are generalizable to other types of university contexts (e.g., predominantly White institutions, historically Black colleges and universities, Native American serving institutions) and future research is needed to clarify this.

Students within this study were asked to reflect only on their most recent undergraduate research experience and indicate if they had authored/coauthored a paper that was either in the review process or had been published as a result of their participation at the moment of the survey. Relying on student self-reports of publishing activities is a limitation of this work. Since publication of research findings takes time which may extend beyond a research program, our measure likely undercounts the number of students who eventually produce papers. It is also the case that some “in review” papers are never published, which could lead to overestimation of publications.

Another limitation of our study is the use of only quantitative methods to assess possible barriers to student publications. Future research on this topic would be advanced through the use of qualitative methods such as in-depth interviews to provide a better understanding of student experiences and publishing research. In prior qualitative research, students have identified mentors as an important component of their research experience (Schwartz, 2012a). The value of the time spent with a student’s mentor and exactly what unfolds in those encounters for first-generation and continuing-generation students, for example, could be better teased out using qualitative methods.

6.2 Practical implications

Targeted interventions for students and faculty mentors should be enacted so that lower social class students do not fall through the cracks and are given the opportunity to contribute their ideas and talents to STEM fields. On the student side, this suggests that targeted interventions designed to augment the cultural capital of first-generation undergraduate researchers could be effective. Instead of looking at deficits, the cultural capital framework makes transparent the mismatch between working-class students and the university setting. While these students may be able to effectively deploy their cultural capital in other settings (e.g., workplace) and may have significant community cultural wealth (Yosso, 2005), their skills may not always translate into the university. As such, student-level interventions could seek to make the invisible rules and pathways in the university visible to students from lower social class backgrounds. For example, students can be taught to ask professors for a W instead of taking the F when family problems derail a semester or approach a faculty mentor when there is no problem, just to make a personal connection. To help students, program coordinators should also encourage or even require mentors to set up regularly scheduled face-to-face meetings with their mentees. Implementing formal programmatic ways of nurturing mentor–mentee interactions that are typically left to the realm of the informal would likely be beneficial for all mentees and may help to level the playing field for students who have less relevant cultural capital when they enter the research experience and are first generation. Program coordinators should consider providing students’ stipends on a sliding scale whereby low-income students could receive more funding based on their needs, which may increase their chances of publishing as it could allow them to spend more time on research.

Interventions for faculty research mentors should include a social class component. Faculty members should be given the tools to be able to recognize how social class privilege is often rewarded within higher education more generally and within faculty–student relationships

specifically. Faculty mentors must become aware of the ways they are likely to reward students who perform in ways that are in line with their own class backgrounds (e.g., with opportunities to publish research), including rewarding students who more comfortably engage with them, ask for mentoring and advice, and display respect and interest through middle-class norms of performing engagement. They must recognize that the norms common in working class and poor communities, for example, of maintaining distance from authority figures (Jack, 2016) and displaying respect by not asking questions that could be perceived as challenging, can easily be misrecognized in terms of a lack of interest or initiative when viewed through middle-class lenses. Faculty mentors should also become sensitized to the ways in which professional expectations that the best research mentees are available every moment of the day may reward middle-class students. These students are more likely to have access to smartphone and computer technology that keeps them in constant contact, and they do not as often negotiate the family and work responsibilities many working class and poor students shoulder. Faculty mentors can also play important roles in leveling the playing field by naming and discussing professional norms with all students and making the unwritten and often unspoken expectations in the workplace concrete.

Undergraduate research mentors can also borrow some ideas from the concept of educative mentoring, used in the training of new science teachers (Bradbury, 2010), to help them be better mentors. This approach involves a two-way flow of information whereby the ideas of both mentor and mentee are used to develop new ideas (for a longer discussion on the promises of using a colearning approach between mentor and mentee, see Gunkel & Wood, 2016). The mentor seeks to find balance in that he/she values the mentee's ideas while not promoting the idea that all ideas are equally valuable; weights the mentee's immediate needs with her/his long term goals; and both discusses and demonstrates best practices in the relevant field (Bradbury, 2010).

These practices, including making social class visible in our mentoring relationships, take time, effort and reflection on behalf of the faculty mentor, who is already busy with other research, teaching and service responsibilities on the faculty treadmill. Given the importance of increasing diversity in STEM in terms of class, race, and gender, institutional support is needed to allow faculty the time and energy needed to advance the next generation of STEM graduates without penalty to their careers or burning out. Schwartz (2012b) highlights the emotional, professional, and financial costs borne by professors, often professors of color, as they mentor students with significant needs in contexts without adequate support. Clearly, institutions need to be willing partners in this goal, releasing faculty from other responsibilities, so that we can work together to level the playing field in STEM.

In closing, we suggest that social scientists studying STEM fields must pay closer attention to the role of social class. Social class has been underemphasized in research and academic parlance surrounding undergraduate research and STEM careers. Students come to college and the STEM pipeline with complex identities that cannot be reduced to gender or race alone. Improving our understanding of how social class intersects with race and gender is an important avenue for future research.

Acknowledgments

We acknowledge Dr. Osvaldo Morera and Sofia De Anda, who helped with the data collection, and the program directors, including Dr. Lourdes Echegoyen, who provided lists of student participants to us. Research reported in this paper was supported by the National Institute of General Medical Sciences of the National Institutes of Health under linked Award Numbers RL5GM118969, TL4GM118971, and UL1GM118970. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

References

- Abel T. Cultural capital in health promotion. In: McQueen DV, Kickbush I, editors *Health and modernity: The role of theory in health promotion*. New York, NY: Springer; 2007. 43–73.
- Adedokun OA, Parker LC, Childress A, Burgess W, Adams R, Agnew CR, ... Teegarden D. Effect of time on perceived gains from an undergraduate research program. *CBE Life Sciences Education*. 2014; 13(1):139–148. [PubMed: 24591512]
- Allison PD. Imputation of categorical variables with PROC MI. *SUGI 30 Proceedings*. 2005; 113(30): 1–14.
- Astin AW, Antonio AL. *Assessment for excellence: The philosophy and practice of assessment and evaluation in higher education*. Lanham, MD: Rowman & Littlefield; 2012.
- Bailey TG. Faculty research productivity. Paper presented at the Minneapolis, MN: Association for the Study of Higher Education Annual Meeting; 1992. Retrieved from ERIC (ED352895)
- Bauer KW, Bennett JS. Alumni perceptions used to assess undergraduate research experience. *The Journal of Higher Education*. 2003; 74(2):210–230.
- Bourdieu P. The forms of capital. In: Richardson JG, editor *Handbook of theory and research for the sociology of education*. Westport, CT: Greenwood; 1986. 241–258.
- Bourdieu P. *Practical reason: On the theory of action*. Stanford, CA: Stanford University Press; 1994.
- Bozick R. Making it through the first year of college: The role of students' economic resources, employment, and living arrangements. *Sociology of Education*. 2007; 80(3):261–285.
- Bradbury LU. Educative mentoring: Promoting reform-based science teaching through mentoring relationships. *Science Education*. 2010; 94(6):1049–1071.
- Breckler J, Teoh CS, Role K. Academic performance and learning style self-predictions by second language students in an introductory biology course. *Journal of the Scholarship of Teaching and Learning*. 2011; 11(4):26–43.
- Carter DF. The impact of institutional choice and environments on African-American and White students' degree expectations. *Research in Higher Education*. 1999; 40(1):17–41.
- Chang MJ, Sharkness J, Hurtado S, Newman CB. What matters in college for retaining aspiring scientists and engineers from underrepresented racial groups. *Journal of Research in Science Teaching*. 2014; 51(5):555–580.
- Cole D, Espinoza A. Examining the academic success of Latino students in science technology engineering and mathematics (STEM) majors. *Journal of College Student Development*. 2008; 49(4):285–300.
- Collins TW, Grineski SE, Shenberger J, Morales DX, Morera O, Echegoyen LE. Undergraduate research participation improves educational outcomes. *Journal of College Student Development*. 2017; 58(4):583–600.
- Conger D, Long MC. Why are men falling behind? Gender gaps in college performance and persistence. *The Annals of the American Academy of Political and Social Science*. 2010; 627(1): 184–214.
- Crisp G, Nora A, Taggart A. Student characteristics, pre-college, college, and environmental factors as predictors of majoring in and earning a STEM degree: An analysis of students attending a Hispanic serving institution. *American Educational Research Journal*. 2009; 46(4):924–942.
- Daniels H, Grineski SE, Collins TW, Morales DX, Morera O, Echegoyen L. Factors influencing student gains from undergraduate research experiences at a Hispanic-serving institution. *CBE Life Sciences Education*. 2016; 15(3)doi: 10.1187/cbe.15-07-0163

- Davis DJ, Warfield M. The importance of networking in the academic and professional experiences of racial minority students in the USA. *Educational Research and Evaluation*. 2011; 17(2):97–113.
- DeBerard MS, Spielmans G, Julka D. Predictors of academic achievement and retention among college freshmen: A longitudinal study. *College Student Journal*. 2004; 38(1):66–80.
- Dennis JM, Phinney JS, Chuateco LI. The role of motivation, parental support, and peer support in the academic success of ethnic minority first-generation college students. *Journal of College Student Development*. 2005; 46(3):223–236.
- Diez Roux AV. A glossary for multilevel analysis. *Journal of Epidemiology and Community Health*. 2002; 56(8):588–594. [PubMed: 12118049]
- Diggle P, Liang KY, Zeger SL. *Longitudinal data analysis*. Oxford, England: Oxford University Press; 1994.
- DiPrete TA, Buchmann C. *The rise of women: The growing gender gap in education and what it means for American schools*. New York, NY: Russell Sage Foundation; 2013.
- Eagan KM Jr, Garvey JC. Stressing out: Connecting race, gender, and stress with faculty productivity. *The Journal of Higher Education*. 2015; 86(6):923–954.
- Enders CK. *Applied missing data analysis*. New York, NY: Guilford Press; 2010.
- Engle J, Bermeo A, O'Brien C. *Straight from the source: What works for first-generation college students*. Washington, DC: Pell Institute for the Study of Opportunity in Higher Education; 2006.
- Engle J, Tinto V. *Moving beyond access: College success for low-income, first-generation students*. Washington, DC: Pell Institute for the Study of Opportunity in Higher Education; 2008.
- Finley AP, McNair T. *Assessing underserved students' engagement in high-impact practices*. Washington, DC: Association of American College and Universities; 2013.
- Forester M, Kahn JH, Hesson-McInnis MS. Factor structures of three measures of research self-efficacy. *Journal of Career Assessment*. 2004; 12(1):3–16.
- Freeman RB, Huang W. Collaborating with people like me: Ethnic coauthorship within the United States. *Journal of Labor Economics*. 2015; 33(S1):S289–S318.
- Garson GD. *Generalized linear models and generalized estimating equations*. Asheboro, NC: Statistical Associates Publishing; 2012.
- Gilmore J, Vieyra M, Timmerman B, Feldon D, Maher M. The relationship between undergraduate research participation and subsequent research performance of early career STEM graduate students. *The Journal of Higher Education*. 2015; 86(6):834–863.
- Girves JE, Zepeda Y, Gwathmey JK. Mentoring in a post-affirmative action world. *Journal of Social Issues*. 2005; 61(3):449–479.
- Gunckel KL, Wood MB. The principle–practical discourse edge: Elementary preservice and mentor teachers working together on colearning tasks. *Science Education*. 2016; 100(1):96–121.
- Halpern N. The impact of attendance and student characteristics on academic achievement: findings from an undergraduate business management module. *Journal of Further and Higher Education*. 2007; 31(2):335–349.
- Heagney M, Benson R. How mature-age students succeed in higher education: Implications for institutional support. *Journal of Higher Education Policy and Management*. 2017; 39(3):216–234.
- Horta H, Santos JM. The impact of publishing during PhD studies on career research publication, visibility, and collaborations. *Research in Higher Education*. 2016; 57(1):28–50.
- Horton NJ, Lipsitz SR, Parzen M. A potential for bias when rounding in multiple imputation. *The American Statistician*. 2003; 57(4):229–232.
- Hoskins SL, Newstead SE, Dennis I. Degree performance as a function of age, gender, prior qualifications and discipline studied. *Assessment & Evaluation in Higher Education*. 1997; 22(3):317–328.
- Hunter A, Laursen SL, Seymour E. Becoming a scientist: The role of undergraduate research in students' cognitive, personal, and professional development. *Science Education*. 2007; 91(1):36–74.
- Hurtado S, Ponjuan L. Latino educational outcomes and the campus climate. *Journal of Hispanic Higher Education*. 2005; 4(3):235–251.

- Inkelas KK, Daver ZE, Vogt KE, Leonard JB. Living-learning programs and first-generation college students' academic and social transition to college. *Research in Higher Education*. 2007; 48(4): 403–434.
- Ishyama J. Expectations and perceptions of undergraduate research mentoring: Comparing first generation, low income White/Caucasian and African American students. *College Student Journal*. 2007; 41:540–549.
- Ito JK, Brotheridge CM. Predicting individual research productivity: More than a question of time. *The Canadian Journal of Higher Education*. 2007; 37(1):1.
- Jack AA. (No) harm in asking class, acquired cultural capital, and academic engagement at an elite university. *Sociology of Education*. 2016; 89(1):1–19.
- Jaeger MM. Does cultural capital really affect academic achievement? New evidence from combined sibling and panel data. *Sociology of Education*. 2011; 84(4):281–298.
- Jones MT, Barlow AE, Villarejo M. Importance of undergraduate research for minority persistence and achievement in biology. *The Journal of Higher Education*. 2010; 81(1):82–115.
- Kahn JH. Predicting the scholarly activity of counseling psychology students: A refinement and extension. *Journal of Counseling Psychology*. 2001; 48(3):344.
- Kim YK, Sax LJ. Student-faculty interaction in research universities: Differences by student gender, race, social class, and first-generation status. *Research in Higher Education*. 2009; 50(5):437–459.
- Kuh GD, Kinzie J, Schuh JH, Whitt EJ. *Student success in college: Creating conditions that matter*. Hoboken, NJ: Wiley; 2010.
- Laurance WF, Useche DC, Laurance SG, Bradshaw CJ. Predicting publication success for biologists. *Bioscience*. 2013; 63(10):817–823.
- Lareau A, Evans SA, Yee A. The rules of the game and the uncertain transmission of advantage: Middle-class parents' search for an urban kindergarten. *Sociology of Education*. 2016; 89(4):279–299.
- Legewie J, DiPrete TA. The high school environment and the gender gap in science and engineering. *Sociology of Education*. 2014; 87(4):259–280. [PubMed: 27857451]
- Lei SA, Chuang N. Undergraduate research assistantship: A comparison of benefits and costs from faculty and students perspectives. *Education*. 2009; 130(2):232.
- Liang K, Zeger SL. Longitudinal data analysis using generalized linear models. *Biometrika*. 1986; 73:3–22.
- Lohfink MM, Paulsen MB. Comparing the determinants of persistence for first-generation and continuing-generation students. *Journal of College Student Development*. 2005; 46(4):409–428.
- Lopatto D, Tobias S. *Science in solution: The impact of undergraduate research on student learning*. Washington, DC: Council on Undergraduate Research; 2010.
- Lopatto D. Survey of undergraduate research experiences (SURE): First findings. *Cell Biology Education*. 2004; 3(4):270–277. [PubMed: 15592600]
- Lopatto D. Undergraduate research experiences support science career decisions and active learning. *CBE Life Sciences Education*. 2007; 6(4):297–306. [PubMed: 18056301]
- Manfreda KL, Vehovar V. Internet surveys. In: Leeuw E, Hox JJ, Dillman DA, editors *International handbook of survey methodology*. New York, NY: CRC Press/Taylor and Francis Group; 2008. 264–284.
- Mau WJ. Characteristics of US students that pursued a STEM major and factors that predicted their persistence in degree completion. *Universal Journal of Educational Research*. 2016; 4(6):1495–1500.
- Morgan SL, Mehta JD. Beyond the laboratory: Evaluating the survey evidence for the disidentification explanation of black-white differences in achievement. *Sociology of Education*. 2004; 77(1):82–101.
- Mwenda MN. Underrepresented minority students in STEM doctoral programs: The role of financial support and relationships with faculty and peers. Doctoral Dissertation. 2010. Retrieved from from ERIC. (881461811; ED521393) and <https://ir.uiowa.edu/cgi/viewcontent.cgi?article=1745&context=etd>

- Nelder J, Wedderburn R. Generalized linear models. *Journal of the Royal Statistical Society, Series A*. 1972; 135:370–384.
- National Survey of Student Engagement. About NSSE. Indiana University; Bloomington, IN: 2015. Retrieved from <http://nsse.indiana.edu/html/about.cfm>
- Ostrove JM, Long SM. Social class and belonging: Implications for college adjustment. *The Review of Higher Education*. 2007; 30(4):363–389.
- Pacifici LB, Thomson N. What do they expect? A comparison of student expectations and outcomes of undergraduate research experiences. *Journal of College Science Teaching*. 2011; 41(1):54.
- Pascarella ET, Pierson CT, Wolniak GC, Terenzini PT. First-generation college students: Additional evidence on college experiences and outcomes. *The Journal of Higher Education*. 2004; 75(3): 249–284.
- Pasupathy R, Siwatu KO. An investigation of research self-efficacy beliefs and research productivity among faculty members at an emerging research university in the USA. *Higher Education Research & Development*. 2014; 33(4):728–741.
- Paterson L, Iannelli C. Social class and educational attainment: A comparative study of England, Wales, and Scotland. *Sociology of Education*. 2007; 80(4):330–358.
- Penn DA. Estimating missing values from the general social survey: An application of multiple imputation. *Social Science Quarterly*. 2007; 88(2):573–584.
- Quimbo MAT, Sulabo EC. Research productivity and its policy implications in higher education institutions. *Studies in Higher Education*. 2014; 39(10):1955–1971.
- Reisel L. Two paths to inequality in educational outcomes: Family background and educational selection in the United States and Norway. *Sociology of Education*. 2011; 84(4):261–280.
- Richardson JTE. Mature students in higher education: Academic performances and intellectual ability. *Higher Education*. 1994; 28:373–386.
- Richardson JTE, King E. Adult Students in Higher Education. *The Journal of Higher Education*. 1998; 69(1):65–88.
- Rodwell L, Lee KJ, Romaniuk H, Carlin JB. Comparison of methods for imputing limited-range variables: A simulation study. *BMC Medical Research Methodology*. 2014; 14(1):57. [PubMed: 24766825]
- Russell SH, Hancock MP, McCullough J. Benefits of undergraduate research experiences. *Science*. 2007; 316(5824):548–549. [PubMed: 17463273]
- Schucan Bird K. Do women publish fewer journal articles than men? Sex differences in publication productivity in the social sciences. *British Journal of Sociology of Education*. 2011; 32(6):921–937.
- Schuster JH, Finkelstein MJ. *The American faculty: The restructuring of academic work and careers*. Baltimore, MD: Johns Hopkins University Press; 2006.
- Schwartz J. There is another world out there: Students of color and undergraduate STEM research. *International Journal of Science in Society*. 2012a; 3(2):35–52.
- Schwartz J. Faculty as undergraduate research mentors for students of color: Taking into account the costs. *Science Education*. 2012b; 96(3):527–542.
- Seymour E, Hunter A, Laursen SL, DeAntoni T. Establishing the benefits of research experiences for undergraduates in the sciences: First findings from a three-year study. *Science Education*. 2004; 88(4):493–534.
- Sirin SR. Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research*. 2005; 75(3):417–453.
- Stephens NM, Hamedani MG, Destin M. Closing the social-class achievement gap: A difference-education intervention improves first-generation students' academic performance and all students' college transition. *Psychological Science*. 2014; 25(4):943–953. [PubMed: 24553359]
- Stuber JM. *Inside the college gates: How class and culture matter in higher education*. Washington, DC: Lexington Books; 2011.
- Swihart RK, Sundaram M, Höök TO, Dewoody JA. Factors affecting scholarly performance by wildlife and fisheries faculty. *The Journal of Wildlife Management*. 2016; 80(3):563–572.

- Syed M, Goza BK, Chemers MM, Zurbriggen EL. Individual differences in preferences for matched-ethnic mentors among high-achieving ethnically diverse adolescents in STEM. *Child Development*. 2012; 83:896–910. [PubMed: 22506789]
- Thiry H, Weston TJ, Laursen SL, Hunter AB. The benefits of multi-year research experiences: Differences in novice and experienced students' reported gains from undergraduate research. *CBE Life Sciences Education*. 2012; 11(3):260–272. [PubMed: 22949423]
- URSSA, Undergraduate Research Student Self-Assessment. *Ethnography and evaluation research*. Boulder: University of Colorado at Boulder; 2009.
- University of Texas at El Paso, Center for Institutional Evaluation Research and Planning. The UTEP common data set 2014. El Paso, TX: Author; 2014. Retrieved from cierp2.utep.edu/CommonDataSets/UTEP%20CDS%202014.pdf
- Van Dijk D, Manor O, Carey LB. Publication metrics and success on the academic job market. *Current Biology*. 2014; 24(11):R516–R517. [PubMed: 24892909]
- Wang M, Degol JL. Gender gap in science, technology, engineering, and mathematics (STEM): Current knowledge, implications for practice, policy, and future directions. *Educational Psychology Review*. 2016; 29(1):119–140. [PubMed: 28458499]
- Weston TJ, Laursen SL. The undergraduate research student self-assessment (URSSA): Validation for use in program evaluation. *CBE Life Sciences Education*. 2015; 14(3):ar33. [PubMed: 26250563]
- Winkler R. Foundations of educational inequality: Cultural capital and social reproduction. *ASHE Higher Education Report*. 2010; 36(1):1–21.
- Yosso TJ. Whose culture has capital? A critical race theory discussion of community cultural wealth. *Race Ethnicity and Education*. 2005; 8(1):69–91.
- Zeger SL, Liang K. Longitudinal data analysis for discrete and continuous outcomes. *Biometrics*. 1986; 42:121–130. [PubMed: 3719049]

FIGURE 1.
Input-Environment-Output Model: Predicting Scholarly Publications among Undergraduate Research Participants

FIGURE 2.

Graphs showing how the relationships for research confidence, months in research, and time with mentor with publishing are significantly moderated by first-generation student status
Note: Results depicted in the graphs are found in Table 3 (columns B, C, and D), and they assume all other variables to be 0, which is the mean for the standardized variables and the reference groups for the dichotomous variables. -1, 0, and 1 on the *x*-axis correspond to one standard deviation below the mean, the mean, and one standard deviation above the mean for each of the three continuous predictors.

TABLE 1

Descriptive statistics for all analysis variables

Continuous variables						
Variable	N	Minimum	Maximum	Mean	Standard deviation	% Missing
Income	190	1	9	3.85	2.130	10.8
Age (in years)	207	17	44	22.77	4.300	2.8
Gained research confidence	202	-3.19	.96	0	1.00	5.2
Time with mentor	211	1	4	2.48	1.212	.9
Months in research	211	0	32.5	15	9.903	.9
Dichotomous variables						
Variable	N	Yes	No	% Missing		
Have a paper under review and/or published	213	53	160	0		
First-generation college student (parents with no college degree)	207	102	105	2.8		
First-generation college student (parents with no college experience)	207	50	156	2.8		
Sex: Male	213	91	122	0		
Latina/o	205	182	23	3.8		
Have regular face-to-face meetings with a mentor	213	72	141	0		
Participation in more than one program	213	56	157	0		

Notes: Income was measured on a 9-point scale ranging from 1 (under \$10,000 per year) to 9 (over \$250,000 per year). Gained research confidence is a scale, created using principal components analysis to combine three variables. Time with mentor was measured on a 4-point scale ranging from 1 (1 hour per week or less) to 4 (4 or more hours per week).

TABLE 2

Breakdown of students' characteristics based the publishing outcome

Dichotomous variables	Published	Not published
First generation	20	82
Continuing generation	32	73
Male	19	72
Female	34	88
Latino/a	45	137
Not Latino/a	7	16
Regular meetings	23	49
No regular meetings	30	111
More than one program	13	43
Only one program	40	117

TABLE 3

Results of generalized estimating equations^a predicting having a paper published and/or under review ($n = 218$): (A) Main effects model, (B) first-generation student interaction with scholarly gains, (C) first-generation student interaction with mentoring variables, and (D) first-generation student interaction with research experience variables

	A			B			C			D		
	<i>B</i>	<i>SE</i>	<i>p</i>	<i>B</i>	<i>SE</i>	<i>p</i>	<i>B</i>	<i>SE</i>	<i>p</i>	<i>B</i>	<i>SE</i>	<i>p</i>
Intercept	-.158	0.223	.477	-.241	0.242	.321	-.244	0.208	.240	-.156	0.246	.525
Income	.202	0.081	.012*	.240	0.085	.005*	.219	0.082	.008*	.185	0.079	.019*
First-generation college student (ref: continuing)	-.327	0.133	.014*	-.306	0.136	.025*	-.244	0.170	.152	-.348	0.151	.021*
Age	.209	0.109	.054	.216	0.107	.043*	.218	0.110	.049*	.228	0.104	.029*
Male (ref: female)	-.157	0.152	.303	-.161	0.141	.254	-.150	0.154	.330	-.136	0.159	.391
Latino/a (ref: non-Latino/a)	-.080	0.205	.695	.008	0.220	.972	-.030	0.201	.883	-.0075	0.219	.732
Research confidence	.046	0.085	.591	.363	0.163	.026*	.068	0.082	.405	.055	0.087	.525
Time with mentor	-.048	0.122	.692	-.037	0.104	.721	.101	0.106	.336	-.052	0.115	.652
Regular face-to-face meetings with mentor	.337	0.134	.012*	.412	0.127	.001*	.456	0.150	.002*	.338	0.130	.009*
Months in research	.297	0.167	.075	.352	0.172	.041*	.307	0.187	.101	.428	0.177	.016*
Participation in more than one program	-.145	0.323	.653	-.261	0.368	.478	-.117	0.363	.748	-.178	0.375	.634
First-generation college student *Research confidence	n/a	n/a	n/a	-.715	0.218	.001*	n/a	n/a	n/a	n/a	n/a	n/a
First-generation college student *Time with mentor	n/a	n/a	n/a	n/a	n/a	n/a	-.353	0.177	.046*	n/a	n/a	n/a
First-generation college student *Regular face-to-face meetings with mentor	n/a	n/a	n/a	n/a	n/a	n/a	-.259	0.349	.457	n/a	n/a	n/a
First-generation college student *Months in research	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	-.276	0.134	.039*

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript

	A			B			C			D		
	<i>B</i>	<i>SE</i>	<i>p</i>	<i>B</i>	<i>SE</i>	<i>p</i>	<i>B</i>	<i>SE</i>	<i>p</i>	<i>B</i>	<i>SE</i>	<i>p</i>
First-generation college student *	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	.083	0.337	.806

^aEach model uses a binomial distribution with a negative log-log function. Income, age, time with mentor, quality of mentor, months in research, and research confidence were included as standardized variables. Only pooled results are shown. *B* represents the parameter estimate, and *SE* means standard error.

* $p < .05$.