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Persisting Gaps: Labor Market Outcomes and Numeracy Skill Levels of First Generation and Multi Generation College Graduates

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Persisting Gaps:

Labor Market Outcomes and Numeracy Skill Levels of First-Generation and Multi-Generation College Graduates

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In the public psyche and in academic discourse, it is widely believed that a college degree is the great equalizer. In other words, social origins may determine educational attainment, but educational attainment (especially a college degree) determines labor market outcomes and membership to the American middle class. This notion is supported by the empirical work of scholars who have replicated this relationship in the US and abroad using nationally representative datasets (Blau and Duncan 1967; Hout 1980; Hout 1985; Torche 2011). This line of research, known in sociology as the "status attainment" tradition, has dominated public and academic understandings of the relationship between social origins, educational attainment (particularly attainment of a college degree), and occupational destinations for half a century. This is why much attention is paid to first-generation college students' transitions into and through college. However, after college, first-generation college graduates become part of a larger group: college graduates.

In addition, status attainment theorists have not incorporated rigorous measures of cognitive skills into models that test how a college degree mediates the relationship between social origins[1] and occupational destinations[2]. In other words, do first-generation and multi-generation college graduates have similar cognitive skills? Moreover, controlling for cognitive skill, do first-generation and multi-generation college graduates have similar labor market outcomes?

This project seeks to understand whether there are latent differences in cognitive skills[3] between first- and multi-generation college graduates and investigate whether there are differences in labor market outcomes between first- and multi-generation college graduates, while controlling for a measure of skill.

Understanding whether there are numeracy level and labor market differences between first- and multi-generation college graduates has important implications for theory and policy. College graduation is understood to be a golden ticket to the American middle class without questioning whether the rewards of higher education differ by social origins. From a policy perspective, this work puts the outcomes of higher education into clearer context. Are colleges places that fill in the final skill gaps between first-generation and multi-generation students? If not, policy makers should consider whether the equity agenda that shapes funding and assessment in the K-12 sector should to extend to higher education.

Our findings confirm some of the pillars of the status attainment paradigm, but also offer some complicating perspectives. First, we find that first-generation and multi-generation college

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[1] Measures of parental education and occupation are traditionally used as proxies for social origins. For this study, highest level of parental education is used to determine if the college graduates in the sample are considered "first generation" or "multi-generation" college goers.

2 Educational attainment has been taken for granted as a proxy for skills, mainly because datasets that contain robust measures of adult skills are rare.

[3] The dataset used for this paper includes measures of literacy, numeracy, and problem solving. We found literacy and numeracy to be most relevant to what we mean by cognitive skills. We ran our analyses for both literacy and numeracy and found that the results were quite similar. Because of non-English speaking immigrant populations, we decided that numeracy would provide a cleaner measure of skills, and our analyses proceed using only numeracy as a measure of skills.

graduates have similar labor market outcomes in terms of monthly earnings, employment, occupational prestige, and rates of holding jobs that match their college major. However, we find significant differences in numeracy scores of college graduates who are first-generation and those who have a college-educated parent. Multi-generation college graduates outperformed their first-generation college graduate peers by significant margins on assessments of numeracy.

We proceed by presenting a brief review of the literature on education and status attainment/social mobility research in the US. We then present our analytical strategy and describe the data. Our findings and discussion follow. Next we discuss possible mechanisms for the gaps in numeracy scores among college graduates. We conclude by presenting some ways to interpret these seemingly incongruent findings: there are numeracy differences among first- and multi-generation college graduates; however, these differences do not seem to lead to real differences in labor market outcomes.

Literature Review

At the center of the status attainment paradigm is the well-documented, empirical relationship between social origins, educational attainment, and social destinations. Status attainment sociologists have demonstrated the strong, positive relationship between social origins and educational attainment (Blau and Duncan 1967; Hout 1980; Hout 1985; Torche 2011; Hamilton 2014). Father's occupation and educational attainment are associated with the occupational outcomes of the child *indirectly* through education (Blau and Duncan 1967). Sewell, Haller, and Portes (1969) built on Blau and Duncan's model by considering individual aspirations, peer group influences, and the effects of significant others when modeling the relationship between occupational attainment and social origins (Sewell, Haller and Portes 1969; Haller and Portes 1973). Both models hold that the association between social origins and social destinations is entirely mediated by the educational attainment of the individual. That is, social background has everything to do with how much education individuals attain; however, it is educational attainment, not family background, which predicts labor market outcomes. Family advantages flow through educational attainment, but family advantages have no direct impact on occupational destinations. Hout succinctly writes:

> Origin status affects destination status among workers who do not have bachelor's degrees, but college graduation ***cancels*** the effect of background status. (Hout, 1988, p1358, emphasis added).

Thirty years later, Florencia Torche asked if the status attainment findings could be replicated using more recent data. In her own words, "Is a College Degree Still the Great Equalizer?" Torche (2011) finds that among college graduates, social background is not predictive of income or occupational prestige. Her findings have bolstered another generation of researchers to view a four-year college degree as "the great equalizer."

The findings of Torche (2011) and other status attainment researchers have been influential in the way that sociologists and scholars of higher education have empirically treated college graduates. Taken at face value, these findings lead social scientists to assume that upon graduation all college graduates are virtually indistinguishable -- that no matter their social origins, college graduates go on to inhabit the same levels of occupational prestige and labor market success.

Despite the paradigmatic role of status attainment theory, some emerging work has begun to examine types of differences that might exist among college graduates. Michael Gaddis' (2014) audit study using identical resumes demonstrates that black and white college graduates from selective and non-selective colleges have differing rates of calls about job interviews.

Qualitative work by Armstrong and Hamilton (2013) chronicles how social background shapes college students' participation in majors, on-campus activities, and ultimately post-college labor market opportunities. Finally, Riviera (2015) shows how social class coupled with college selectivity shapes the career trajectories of college graduates. In each of these examples, sociologists are beginning to add nuance to our understanding of the role of colleges in social mobility.

Furthermore, there is no shortage of literature about the achievement differences by social class of students at every level: students entering kindergarten through the end of high school have measurable, class-defined outcome differences (for a review see Reardon 2011 and 2013). There is a growing literature on the horizontal stratification of the types of colleges that students attend by class: students from working-class backgrounds are more likely to attend community colleges or large regional campuses; socially advantaged students are more likely to attend selective universities and public, research-intensive flagship campuses (Mullen 2012; Carnavale 2013). When students from differing class backgrounds attend the same colleges, social class defines students' experiences and pathways through college (Hurst 2006; Armstrong & Hamilton 2013).

Specifically, we will investigate the following research questions:

RQ1. Is there a difference in numeracy scores between first-generation college graduates and multi-generation college graduates?
RQ2. Is college graduate generational status related to employment outcomes after controlling for numeracy score?

This paper contributes to an emerging literature that explores differences among college graduates by social background[4]. Additionally, this paper tests for differences in numeracy skills between first- and multi-generation college graduates. This analysis is unique in that the few datasets provide measures of skills for adults, and little is known about whether skill differences between first- and multi-generation college graduates persist into adulthood.

Data & Methods

This study uses the United States sample of the Program for the International Assessment of Adult Competencies (PIAAC), a nationally representative survey of 5,000 adults that was collected in 2012. The purpose of PIAAC is to comparatively assess basic skills and competencies of adults in twenty-four nations. The data contain a comprehensive set of background variables, educational and workplace information, variables on the use of technology, and several measures of cognitive skills including literacy, numeracy, and problem solving. We ran our analyses for both literacy and numeracy and found that the results were quite similar. Because of the presence of non-English speaking immigrant populations, we decided that numeracy would provide a cleaner measure of skills, and our analyses proceed using only numeracy as a measure of skills. PIAAC's measures of adult numeracy combined with the variety of measures of economic outcomes and demographic characteristics offer a unique opportunity to explore our research questions.

Sample

[4] There is a robust literature looking at first-generation college students as they apply and transition into college. Literature on the rates of first-generation college student persistence and engagement is rich and well documented. However, the literature on first-generation students' outcomes after graduation is much more sparse. Researchers tend to consider first-generation students post-college as members of a larger group: college graduates.

The sample for this study consists of college graduates between the ages of 25 and 54 in the United States. We examine only college graduates because research on college graduates' economic outcomes rarely disaggregates by social origins, and when it does, it does not include measures of skills. Addressing the trends of participants without a college degree would be a separate analysis. We chose to exclude those below 25 years of age for several reasons. Participants below 25 are less likely to be in the workforce, which is an important qualifier for our sample. In addition, we wanted to allow for students to have time to complete their bachelor's degree[5]. Participants over age 54 were dropped because they were significantly more likely to be out of the workforce than those 54 and under. Table 1 provides the descriptive statistics for all age groups by employment status. Given that our study focuses on employment outcomes, we chose to remove all respondents who were not employed. We removed respondents who did not earn a baccalaureate degree because our research questions focus on differences in parental education and skills upon completion of at least a bachelor's degree. Finally, sixty-six observations were removed due to missing numeracy scores, for which we were not able to impute. The resulting sample, consisting of 1,035 respondents, was used for all models except for those requiring employment, such as earnings, job prestige, and occupation-major match. Models with dependent variables that required employment used a sub-sample of employed respondents containing 919 observations. One limitation of restricting the sample, since the survey was not designed as a random sample of 25-54 year olds with baccalaureate degrees, is that our results may not be representative of all adults with those characteristics.

Table 1. Percentage of observations by employment status

Age	Employe	Unemployed	Out of

[5] A majority of students that earn a bachelor's degree do so by age 25 (Spreen, 2013)

	d		Workforce
16-19	44%	19%	36%
20-24	71%	13%	16%
25-29	81%	9%	10%
30-34	79%	7%	15%
35-39	82%	7%	11%
40-44	79%	7%	14%
45-49	79%	6%	15%
50-54	78%	6%	16%
55-59	70%	6%	25%
60-65	57%	4%	39%
Total	73%	8%	19%

After removing these observations, there was still a large amount of missing data for several variables including parental education and earnings. Missing data is problematic when it is not missing at random, which occurs in the PIAAC dataset, as those with low education and numeracy scores are significantly more likely to be missing information. A common strategy to handle missing data is multiple imputation, which uses the information available to the researcher to fill in missing information with plausible values (Allison, 2001). This strategy is called multiple imputation because it creates several versions of the missing data, adding some random variation to each imputation. While a single imputation may not be representative of each individual observation, combining five or more imputations provides an accurate representation of the actual values (Rubin, 2004).

Imputation was complicated by the fact that several of the latter research questions examine economic outcomes, which can only be calculated for those who have jobs, with the exception of the outcome variable for employment. In particular, we did not want to impute earnings for individuals who were not employed. Therefore, we employed a two-step strategy by creating five imputations for all observations to use with models 1-3, then we created five imputations using only observations for those who were employed during the survey. Following the advice of Allison (2002), all variables used in the regression models were used in the imputation process, including parental education, race/ethnicity, educational attainment, gender, immigrant status, and age. The variable that counted the number of books in the home was included in the imputation model due to its high correlation with parental education. In the second step, earnings, job prestige, number of hours worked per week, number of employees at workplace, flexibility of job responsibilities, parental education, books at home, and race/ethnicity were imputed using educational attainment, gender, immigrant status, and age. Number of employees in the workplace, flexibility of job responsibilities, and books at home were added to the imputation model because they correlated highly with variables that were being imputed. In addition, since we imputed for a dependent variable, it is imperative to add variables that will not be used in the analysis; otherwise, the imputed values for the dependent variable would add no new information since they are a function of the independent variables in the model (Allison, 2002). A chained imputation process was used, which means that the process first filled in values for the variable with the least missing data, then used that variable to help fill in the variable with the second least missing data, and so on (Rubin 2004). A random seed was used for both imputation processes to ensure that the imputations could be replicated in the future. Descriptive statistics for imputed variables were analyzed to ensure that the resulting imputed variables were stable across imputations.

Background Characteristics

Gender refers to whether a respondent is female or not, while *immigrant* refers to whether a respondent was born in a foreign country or not. *Race/ethnicity* is categorized with four dummy variables: black, Asian, Hispanic, and other race, with white serving as the reference group. *Age* is grouped in five-year intervals beginning with the 25-29 group and ending with the 50-54 group. Each age group was recoded as a dummy variable, with the 25-29 age group serving as the reference group. Education, skills, and economic outcomes have been shown to vary by background characteristics by numerous research studies (Carnevale, Rose, & Cheah, 2011; Ehrenberg & Smith, 1985).

Parental education is the key background variable that we use as proxy for students' early advantages and their social class.[6] About forty percent of the sample had a parent with a bachelor's or higher-level degree. We consider this group to be *multi-generational* college graduates, since they have multiple generations of college completion in their families. The individuals in the sample that do not have a parent with a bachelor's or higher-level degree or higher we refer to as *first-generation* college graduates, because they are the first in their immediate families to attend college. This differs from a person's own education level, which we refer to as ***educational attainment.*** Educational attainment was operationalized as having earned a bachelor's degree or not. Educational attainment was used to create the sample, but it is not in any of the models. Both parental education and educational attainment have been shown

[6] While social class is typically determined by a measure of parental education or personal education and a measure of income or family wealth, participants' earnings is a dependent variable and there is no measure of family wealth in PIAAC. Therefore, we use parental education as our sole measurement of social class.

to influence cognitive skills and economic outcomes (Card, 1999; Carnevalle, Rose, & Cheah, 2011; Haveman & Smeeding, 2006; Ounha & Heckman, 2007).

Numeracy is included as an independent variable in models predicting economic outcomes. For the regression model in Table 1, numeracy is the dependent variable. Used as the sole measure of cognitive skills for this study, numeracy is defined as “the ability to use, apply, interpret, and communicate mathematical information and ideas, in order to engage in and manage the mathematical demands of a range of situations in adult life” (OECD, 2015). Cognitive skills have been shown to influence economic outcomes such as earnings and employment (Green & Riddell, 2002; Hanushek & Woessmann, 2008). Identical models were run using literacy as the measure of cognitive skills, yielding similar results. However, we opted to include only numeracy to limit the confounding nature of literacy and English language proficiency, particularly for immigrants that are likely to have artificially low literacy scores simply due to their status as non-Native English speakers. Similarly, we chose not to use problem solving because a number of participants chose not to take the test due to limited computer or English proficiency. All cognitive skills were measured using a computer-based adaptive instrument designed to test the proficiency level of participants in a given cognitive area. Participants that passed computer-based assessment tests were routed to one of three possible tests, each taking about fifty minutes to complete. Half of respondents received a combination of literacy and numeracy tasks, 33% received problem solving with either literacy or numeracy, and 17% were given only problem-solving sections. This means not all participants were given tests in all cognitive areas. To fill in missing values, participants were assigned “plausible values” for questions they did not answer based on their responses to other questions and background characteristics. Additional information on the questionnaire or sampling design, as well as the plausible value process, can be found in the PIAAC technical report (OECD, 2015).

Economic Outcomes

Four economic outcome variables were used in this study: employment status, earnings, occupational prestige, and major-employment match. *Employment status* refers to whether a respondent was employed at the time of the survey, while *earnings* represents the gross monthly earnings of the respondent. *Occupational prestige* is a numeric value representing the prestige of an individual's job that falls between a score of 15 (e.g. food preparation assistant) to 89 (e.g. medical doctor) (Ganzeboom & Treiman 1996). Occupational prestige is a good supplementary measure because, while employment and earnings can change from month to month, occupational status is a much less volatile measure of economic well-being. Over time and across regions, the American occupational structure is surprisingly stable. *Major-employment match* is operationalized as a match between the major field of a person's degree (bachelor's degree and above) and their industrial classification. For example, respondents who studied engineering and are working in an engineering industry were considered a match, while respondents who studied engineering but are working in a business industry are considered a non-match. This variable is a crude match between major and industry type, as some majors do not track well into a specific industrial field. For example, a respondent with a degree in science could have a job in the manufacturing of food, beverages, or chemicals, but these industrial fields are more closely aligned with engineering, manufacturing, and construction. Similarly, students with general programs of education cannot be directly classified into any industrial classification. However, the major-employment match variable does provide a picture into the applicability of a given major in the economy. The complete matching process can be found in Appendix B.

Analytic Strategy

Appendix A provides a list of variables, their PIAAC variable name, and a brief description of the variable. The research questions are mainly descriptive, so this project uses descriptive and associative methods such as ordinary least squares and logistic regression for data analysis. Our dependent key variables for regression models are educational attainment, numeracy skills, and work-related outcomes (employment status, match between major and industry, occupational prestige, and income). Educational attainment and numeracy serve as dependent variables in earlier models and independent variables in later models. For all analyses, we controlled for ascriptive background variables including race/ethnicity, age, gender, immigrant status, and parental education. These covariates allowed us to account for differences and reduce error based on background characteristics of individual respondents.

Linear regression, also referred to as ordinary least squares (OLS) regression, is the preferred method for analyses with a continuous dependent variable, such as numeracy, occupational prestige, and income (Agresti, 2007). The functional form of the linear regression models can be described as:

$$Y_1 = \beta_0 + \beta_{1xi} + \beta_{2xi} + \varepsilon\ ;$$

where β_{1xi} is a vector of independent variables of interest, β_{2xi} is a vector of control variables, and ε is the error term. We used the 10 plausible values and the OECD SAS macro for all analyses that include numeracy scores.

Logistic regression is the preferred method of analysis with binary outcomes, such as earning a bachelor's degree, employment status, and major-job match. Our logistic regression models can be summarized by the following equation:

$$\log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 x_i + \beta_2 x_i;$$

where β_{1xi} is a vector of independent variables of interest, and β_{2xi} is a vector of control variables.

Appropriate weights and replication were accounted for in each model using the *svy* command in STATA for models without plausible values and the *repest* macro provided by the OECD for models with plausible values. The svy command in STATA produced identical outcomes to the repest macro provided by the OECD, but was found to be simpler and quicker in models with no plausible values. In addition, the STATA user-generated command *mira* was used to account for multiple imputations of missing data. The mira command runs a separate regression for each imputed dataset, then combines the imputed datasets using Rubin's rules for imputation (Rubin, 2004). The mira command was also preferred because it allows for the use of both repest and svy. For models using plausible values, the repest command runs Rubin's rules across the 10 plausible values for numeracy for each imputed dataset, then mira runs Rubin's rules to combine the results across the imputed datasets. This means that models with plausible values are averaged across 50 models.

Models

The general strategy for the models in this study was to build a case for relationships between parental education, numeracy, and labor market outcomes. Therefore, we began by testing relationships with numeracy as the dependent variable, then built larger models using numeracy as an independent variable to predict labor market outcomes. In using the term prediction, we do not imply causation, but rather the relationship between the predictor variables and the dependent variables.

Table 2 provides a summary of the regression models run, including the type of regression, dependent variables, and independent variables used. Model 1 uses the entire sample described above. In models 2 and 3, equations using employment as their dependent variable use the entire sample; equations using income, major-occupation match, and occupational prestige use the subset of respondents who were employed.

Table 2. Models used in analysis

Model	Regression Method	Dependent Variable	Independent Variables
Model 1	Linear	Numeracy	Parental education
Model 2	Linear and Logistic	Economic outcomes	Parental education
Model 3	Linear and Logistic	Economic outcomes	Parental education, numeracy

Findings

Means and crosstab findings

Our descriptive findings are displayed in Table 3. There are significant mean differences in numeracy scores by social background. For example, among college graduates who hold a BA, those with parental education advantages on average scored 17 points higher in numeracy than their college-graduate peers without parental education advantages.

Table 3. Descriptive statistics with weighted percentages and means

	Multi-Generation		First-Generation	
Variable	Count	Weighted %	Count	Weighted %
Race				
Asian	73	12.02%	42	12.44%
Black	52	6.97%	48	10.00%
Hispanic	36	5.01%	32	9.28%
White	494	76.00%	258	68.29%
Age				
25-29	146	21.19%	50	12.78%
30-34	112	16.61%	56	13.49%
35-39	121	20.06%	53	14.21%
40-44	108	16.41%	64	17.00%
45-49	84	13.18%	70	20.38%
50-54	84	12.56%	87	22.14%
Immigrant Status				
Non-Immigrant	539	81.40%	306	79.21%
Immigrant	116	18.60%	74	20.79%

Gender				
Male	278	44.81%	160	46.43%
Female	377	55.19%	220	53.57%
Employment Status				
Not Employed	77	11.61%	39	10.94%
Employed	578	88.39%	341	89.06%
Major Occupation Match				
Match	420	28.05%	231	65.86%
No Match	165	71.95%	116	34.14%
First-Generation Status	655	63.29%	380	36.71%[CE3] [MU4]

	Weighted Mean	
	Non-First-Generation	First-Generation
Numeracy	303	287
Earnings	$7,095	$6,495
Prestige	59	57

Note: Weighted percentages were used to account for sampling process.

There were no significant differences in rates of unemployment between multi-generation and first-generation college graduates (Table 3). Occupational prestige between first- and multi-generational college graduates was not significantly different. Sociologists use occupational prestige as a measure of social standing because occupations, rather than earnings, tend to be more stable measures of social and economic well-being. While income can change (sometimes drastically) from month to month, occupation and occupational prestige are more stable indicators of social standing and economic security. Finally, there is a large difference in monthly earnings between first-generation college graduates and their multi-generation peers. Those whose parents attended college, on average, earned about $600 more a month. This difference in earnings between first-generation and multi-generation college graduates does not hold when graduate school is controlled for. We hypothesize that this difference in means can be attributed to the fact that multi-generation college graduates are more likely to go to graduate school (and those with graduate degrees tend to earn more). In later analyses we correct for this by breaking out the category of college graduates into those who have BAs and those with graduate degrees. These descriptive findings are from the crosstabs analysis and do not contain any controls; however, they foreshadow many of the relationships we found in the multivariate regression analyses.

Regression model findings

The first model aims to answer the first research question: Is there a difference in numeracy scores between first-generation and multi-generation college graduates? We see that parental education has lasting effects on adult numeracy proficiency. Among first-generation college graduates, numeracy scores lagged on average eleven points behind their multi-generation college graduate peers. Each competency level in PIAAC spans fifty points, so the difference of eleven points on average is about a quarter of a competency level (barring that the difference does not span competency levels). First-generation college students, controlling for race, age, gender, and immigrant status, enter the labor market with significantly lower levels of numeracy than their multi-generation college graduate peers. Interestingly, those adults with graduate education had even higher numeracy scores than their peers that stopped their education after a BA. For college graduates, additional years of graduate school added an average of 14 to 19 extra points (Model 1).

Our next models test for differences in a variety of labor market outcomes, including rates of unemployment, income, occupational prestige, and major-occupation match. Here our findings are more aligned with the conclusions of the status attainment paradigm -- we did not find measurable differences between first- and multi-generational college graduates across these four labor market outcomes. Findings for the labor market outcomes are displayed in models 2, 3, 4 and 5.

Monthly income was not significantly different between first- and multi-generational college graduates when we controlled for numeracy and social background indicators. However, monthly income did differ dramatically between older and younger cohorts and those who completed just a BA and those who earned higher degrees. Interestingly, among college graduates, numeracy skills were not a significant predictor of earnings (Model 2).

We find no differences between first-generation and multi-generation college graduates in the prestige status of their occupations. However, those with higher numeracy skills and a college degree are more likely to report having occupations with high levels of prestige (Model 3). We find a similar pattern for measures of employment. While numeracy score was positively associated with employment, multi-generation college graduate status was not a significant predictor of being employed or unemployed (Model 4). Furthermore, first- and multi-generation college graduates did not differ in their likelihood to be employed in a job that matched what they studied in school (Model 4). We find that none of the background characteristics (apart from gender) were predictive of the match between major and occupation (Model 5). We were not surprised to see that as workers gained more education and perhaps specializing in a field, they were more likely to have a match between their current occupation and major. In these key labor market outcomes (earnings, rates of employment, occupational prestige, and major-occupation match), first- and multi-generation college graduates were statistically indistinguishable. In fact, status attainment scholars who argue that attaining a college degree ameliorates social background disadvantages would be quite heartened to see evidence of that theory within these findings.

Interestingly, despite the differences that we find in numeracy between first- and multi-generation college graduates, we do not find differences in rates of occupational prestige, unemployment, earnings, or major-occupation match between these groups.

Discussion

The findings presented here are a “cup half full” or a “cup half empty.” The positive findings are that first-generation college graduates, in many ways, look very much like multi-generation college graduates. As the status attainment paradigm suggests, first-generation college graduates in our sample were as likely as their multi-generation peers to hold prestigious occupational positions and earned similar monthly salaries. Furthermore, first-generation college graduates were just as likely as their multi-generation peers to be employed and to be working in jobs that matched their college major.

However, first-generation college graduates are not entirely indistinguishable from their peers from multi-generational college graduate families. Their average numeracy scores lag behind their multi-generational college graduate peers by 15 points or the equivalent of more than two years of schooling (OECD PIAAC, 2014).

Conclusion

The purpose of this work is not to call out the shortcomings of first-generation college graduates. Rather, our hope is to highlight all the ways that first-generation college graduates are succeeding despite their early disadvantages.

The purpose of this paper is also to add nuance to the central claim of the status attainment tradition. We find that attaining a college degree ameliorates some aspects of social background advantages, but in other arenas, social background advantages persist despite educational attainment. This finding contributes to a more complicated picture of universities, not solely as places that confer middle-class advantages, but as places that are themselves stratified and produce stratified outcomes. This work provides some empirical support to the recent scholarship that has begun to describe the ways that universities are stratified by class, both between and within universities (Mullen 2012; Armstrong & Hamilton 2013; Carnavale 2013).

Additionally, sociologists and scholars of higher education have established that there are class differences in measures of academic skill upon entering university, i.e. first-generation college students enroll with lower numeracy scores (Reardon 2011; Reardon 2013). Hence, there should be no surprise that we find numeracy skill differences by social background among college graduates. This work is an attempt to add nuance to the post-college conversation.

Having parents with a college degree is a social advantage associated with higher numeracy scores when students enter college. This work suggests that those differences persist after college and into adulthood.

This work may shed light on Florencia Torche's (2011) finding that social background differences impact graduate school admission and attendance. Since graduate and professional schools tend to rely on standardized test scores when making admissions decisions, our finding about social class differences in numeracy may help to explain that pattern. First-generation college graduates have lower numeracy scores, which are likely to be reflected by the GRE and other assessments used to determine entry into graduate school.

Finally, what is perhaps most interesting about this set of findings is that first-generation college graduates inhabit the same types and levels of occupations as their multi-generational college graduate peers. We see at least one plausible explanation to understand this finding: there may be important institutional differences in the colleges from which first- and multi-generation BA holders graduate. Future work should control for institutional type and quality. Perhaps first-generation college students who attend rigorous, high-quality colleges and universities do just as well as their multi-generation peers. PIAAC does not provide any data on where students went to college (the name of the institution or its characteristics), so it is possible that the differences we are highlighting might disappear if institution were controlled for (see Arum & Roksa 2014 for an example where skill differences disappear when institution is controlled for). We encourage the OECD and NCES to consider adding more questions about the type of higher educational institution attended to PIAAC's background questionnaire in order to allow researchers to investigate the possible impact of type of college on first- and multi-generation college graduates' outcomes.

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Appendix A: Variable identification

Common Name	PIAAC Variable Name	Description
Age	ageg5lfs	Age grouped into 5-year bands
First-generation	Derived from pared	0 = At least one parent has earned tertiary education, 1 = Neither parent has earned tertiary
Female	gender_r	0 = Male, 1 = Female
Immigrant	Derived from j_q04a	0 = Non-immigrant, 1 = First-generation immigrant
Race/Ethnicity	racethn_5cat	Recoded into dummy variables for Hispanic, White, Black, Asian. Other race dropped.
Numeracy	pvnum1 - pvnum10	Plausible value numeracy score
Earned Bachelor's Degree	Derived from edcat7	0 = Neither parent has education above upper secondary, 1 = At least one parent has above upper-secondary education level
Employed	Derived from c_d05	0 = Not employed or not on job market, 1 = Employed
Monthly Income	earnmthallus_c	Monthly income (continuous)

Degree Occupational Match	Derived using isic2c and b_q01b	0 = No match between area of study and industry, 1 = Match between area of study and industry. See appendix 1 for details on matching process.
Occupational Prestige	Derived	Occupation codes converted into scores using (CITE)

Appendix B
Coding Strategy for Matching B_Q01B and ISIC2C

B_Q02C Value	ISCED Fields of Education	ISIC2C Value (International Standard Industrial Classification 2-Digit Code)
0 General programmes	Basic programmes Literacy and numeracy Personal development	
1 Education	Teacher training & Education Science	85 - Education
2 Humanities & Arts	Arts Humanities	90 - Creative, arts and entertainment activities 91 - Libraries, archives, museums and other cultural activities
3 Social Sciences, Business & Law	Social and behavioral science Journalism & information Business & administration Law	69 - Legal and accounting activities 70 - Activities of head offices; management consultancy activities 73 - Advertising and market research
4 Science	Life sciences minus other allied Physical Science Mathematics & Stats Computing	72 - Scientific research and development
5 Engineering, manufacturing, construction	Engineering & environmental protection Manufacting & processing Architecture & building	05 - Mining of coal and lignite 06 - Extraction of crude petroleum and natural gas 07 - Mining of metal ores 08 - Other mining and quarrying 09 - Mining support service activities 10 - Manufacture of food products 11 - Manufacture of beverages 12 - Manufacture of tobacco products 13 - Manufacture of textiles 14 - Manufacture of wearing apparel 15 - Manufacture of leather and related products 16 - Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials 17 - Manufacture of paper and paper products 18 - Printing and reproduction of recorded media

		19 - Manufacture of coke and refined petroleum products 20 - Manufacture of chemicals and chemical products 21 - Manufacture of basic pharmaceutical products and pharmaceutical preparations 22 - Manufacture of rubber and plastics products 23 - Manufacture of other non-metallic mineral products 24 - Manufacture of basic metals 25 - Manufacture of fabricated metal products, except machinery and equipment 26 - Manufacture of computer, electronic and optical products 27 - Manufacture of electrical equipment 28 - Manufacture of machinery and equipment n.e.c. 29 - Manufacture of motor vehicles, trailers and semi-trailers 30 - Manufacture of other transport equipment 31 - Manufacture of furniture 32 - Other manufacturing 33 - Repair and installation of machinery and equipment 35 - Electricity, gas, steam and air conditioning supply 41 - Construction of buildings 42 - Civil engineering 43 - Specialized construction activities 71 - Architectural and engineering activities; technical testing and analysis
6 Agriculture	Agriculture Vetinary	01 - Crop and animal production, hunting and related service activities 02 - Forestry and logging 03 - Fishing and aquaculture 75 - Veterinary activities
7 Health & Welfare	Health Social Services	78 - Employment activities 84 - Public administration and defence; compulsory social security 86 - Human health activities 87 - Residential care activities 88 - Social work activities without accommodation

8 Services	Personal services Community sanitation and labour protection & security Security Services Transport services	36 - Water collection, treatment and supply 37 - Sewerage 38 - Waste collection, treatment and disposal activities; materials recovery 39 - Remediation activities and other waste management services 45 - Wholesale and retail trade and repair of motor vehicles and motorcycles 46 - Wholesale trade, except of motor vehicles and motorcycles 47 - Retail trade, except of motor vehicles and motorcycles 49 - Land transport and transport via pipelines 50 - Water transport 51 - Air transport 52 - Warehousing and support activities for transportation 53 - Postal and courier activities 55 - Accommodation 56 - Food and beverage service activities 77 - Rental and leasing activities 79 - Travel agency, tour operator, reservation service and related activities 80 - Security and investigation activities 81 - Services to buildings and landscape activities 91 - Libraries, archives, museums and other cultural activities 92 - Gambling and betting activities 93 - Sports activities and amusement and recreation activities 95 - Repair of computers and personal and household goods 96 - Other personal service activities
No classification		74 - Other professional, scientific and technical activities 82 - Office administrative, office support and other business support activities 97 - Activities of households as employers of domestic personnel 98 - Undifferentiated goods- and services-producing activities of private households for own use 99 - Activities of extraterritorial organizations and bodies