

# Long-term Effects of STEM Enrichment Programs on Wages Among Under-Represented Minority Students

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## Abstract

This study focuses on the increasing disparities in STEM education achievement and long-term wage earnings of under-represented minority groups. As part of national efforts to improve the diversity of the STEM workforce, this study uses longitudinal data from the University of Houston's Education Research Center (UH-ERC) to examine the effect of participation in a STEM-focused intervention program (Houston-Louis Stokes Alliance for Minority Participation) on wage earnings across students from traditionally under-represented groups. Data analysis consisted of propensity score matching analysis, followed by an ordinal logistic regression model to measure program participation effects on wage earnings. Findings indicate a significant negative association between participation in the STEM intervention program and long-term wage earnings. Results highlight the role of structural racism and human capital on perpetuating achievement and wage gaps across race and socio-economic status. Recommendations focus on career preparedness as a tool to increase the human capital of under-represented groups and institutional shifts in policy and program components that strive to reduce the impact of structural racism on this subpopulation of students.

## Introduction

Using longitudinal data from the University of Houston's Education Research Center, this study aims to examine the effect of participation in the National Science Foundation-funded Houston-Louis Stokes Alliance for Minority Participation (H-LSAMP) on wage earnings across students from traditionally under-represented minority backgrounds. H-LSAMP was founded in 1998 to address racial disparities in STEM degree production nationwide. The Alliance currently consists of five local state universities: one Historically Black College/University (HBCU) and four Hispanic-Serving Institutions as defined by the U.S. Department of Education. The program has run continuously for over 20 years with support from the National Science Foundation, institutional support, corporate sponsors, and private donors. Between 2004 and 2020, the program graduated 2,044 students with bachelor's degrees (Ghazzawi et al., 2022a). Of these graduates, 50.3% identified as either Black or Latinx (Ghazzawi et al., 2022a). Degrees in Engineering account for 34% of the awarded degrees, computer/technology for 6%, and natural sciences and mathematics for 51% (Ghazzawi et al., 2022a).

Oversight of the Alliances activities has rotated between two of the consortium institutions. The designated lead institute coordinates the financial management of the NSF grant, handles reporting requirements, organizes steering committee meetings, and coordinates site visits and external evaluation of the program. Each member institute manages additional funding specific to its campus and implements the program on its campus. The programs vary slightly on campus, but the core concept and mission are consistent across all institutes.

Supported by empirical evidence on collaborative learning environments conducive to minoritized student engagement and academic integration (e.g., Treisman, 1992), H-LSAMP works to reduce achievement gaps within the STEM field by addressing two of the most pressing needs among minority students: academic support and financial need. The program is designed to support students through the transition from high school to graduation with a Bachelor's degree in a STEM field. The programs work to recruit students from high schools with high minority enrollments through interactions with high school counselors and college recruitment events, and STEM-specific competitions and camps. Summer bridge programs for entering first-year students provide intensive math prep for calculus readiness, advice on habits and behaviors, and resources needed for college success. These summer programs provide students with peer mentors and contacts with faculty and staff, so they have a built-in community when they begin their fall semesters. In addition to the academic support to assist students in graduating successfully, a significant component offered to all H-LSAMP scholars is preparation for careers or advancement to graduate/professional level programs. Career preparedness efforts undertaken by partner institutions include skill-building in competency building, self-efficacy skills, and financial planning to assist URM students in entering and successfully moving up through the

STEM career pipeline. Financial support is provided through renewable stipends contingent upon continued active participation in the H-LSAMP program. Participants typically provide at least three hours of service to the learning community weekly. This service can be a peer facilitator for a peer-led team-based active learning supplemental instruction workshop, a tutor, a computer lab assistant, an office aid, or a peer mentor. Alternatively, they may work in a research lab to gain relevant hands-on experience.

Of the 2,044 graduates (2004-2020), 368 (18%) completed advanced degrees: Master's, Ph.D., or Pharmacy/Optometry/Medical degrees in Texas. Our data set could not capture students completing advanced degrees outside Texas. Of these students, 133 (37%) are Black. For Master's recipients, 22% are Latinx (Ghazzawi et al., 2022b).

Detailed analysis of outcomes for one Hispanic-Serving and Asian-Serving Institute in the Houston Alliance demonstrated that students who entered the LSAMP program through the summer bridge were more likely to graduate and more likely to graduate in STEM fields than students who were matched along a set of baseline characteristics (age, gender, race, SAT math scores, and major) who did not participate (Ghazzawi et al., 2022a). Specifically, Hispanic students participating in the program had a significantly higher first semester GPA and final cumulative GPA than the matched non-participants. However, the difference for African American students was not significant. Participants in the program were 3.46 times more likely to complete a STEM degree than non-participants. They had significantly higher grades in Chemistry I and Biology I courses, although, despite the extra emphasis on math, grades in Calculus I were not higher (Ghazzawi et al., 2022a).

## Literature Review

Racial disparities in educational attainment in Science, Technology, Engineering, and Mathematics (STEM) continue to be a national concern (Eagan et al., 2013; Foltz et al. 2014; NCES, 2018; Wimpelberg, 2008). As the U.S. population grows increasingly diverse, the proportion of African American and Latinx STEM graduates lags behind population demographics (Allen-Ramdial & Campbell, 2014; National Science Foundation, 2019). In recent years, higher education institutions have made significant strides in intervention efforts to increase the recruitment, retention, and engagement of under-represented minority students enrolled in STEM fields. Although these efforts have resulted in positive outcomes concerning STEM degree attainment, few studies investigate the outcomes of such interventions on the wage earnings of minority students.

## The Role of Structural Racism on the Racial Wage Gap

Studies focusing on the racial wage gap in STEM rely on human capital and labor market theories to investigate the factors contributing to racial disparities in pay. Broyles and Fenner (2010) conducted a study that examines the impact of human capital on the racial wage gap in STEM undergraduates. Using data from the American Chemical Society, which included a sample of male chemists, the study analyzed labor market earnings as a function of several socio-demographic and labor market characteristics such as race, education, field of work, and region of work, among others. Their study found that after controlling for the labor market and socio-demographic characteristics, minority chemists earned significantly lower than their White counterparts. Results conclude that racial differences in human capital contribute to the racial gap and can be primarily attributed to racism and the perceived value of human capital that STEM workers from minority backgrounds contribute, compared to White STEM workers (Broyles & Fenner, 2010). These results support a rich discourse of literature that discusses the role of systemic racism that manifests widely in STEM disciplines and is perpetuated by institutional policies and practices that attempt to “fix” or change URM students to improve their chances of succeeding through the STEM pipeline while ignoring their role in perpetrating such structures (McGee, 2020, National Academics of Sciences, Engineering, and Medicine, 2019; Zambrana et al., 2017). STEM professions have been widely acknowledged as having a biased and “survival of the fittest” culture, essentially setting up disadvantaged minority students for failure (Leath & Chavous, 2018). Higher education institutions utilize the leaky pipeline in their recruitment goals, which centralize recruiting a high number of URM students into STEM fields and using financial and academic support to increase the graduation and retention of these students. However, this approach deflates and/or ignores the role of structural racism and racial disparities, which continue long after URM students have graduated from their respected STEM fields, and explains why URM students drop out at a higher level and earn significantly lower than their White counterparts (Turk-Bicaki & Berger, 2014). These findings and the role of structural racism in promoting wage inequities are important to consider as a backdrop and foundation to further discussion on wage disparities in STEM.

## Factors Associated with Higher Wage Earnings in STEM

Research has consistently shown a significant wage premium associated with STEM fields (Blackburn, 2004; Cheeseman Day & Martinez, 2021; Tobias & Li, 2003). Findings show that the wage benefit associated with majoring in a STEM field ranges from 5-28%, with high achieving students benefitting from increased earning benefits (Olitsky, 2013; Thomas, 2000). Wage differentials refer to differences in wages between comparison groups. It is a way to look at earnings while considering chosen factors such as training and skills between or across groups or to review the wages of workers with similar skills and jobs but across geographic regions. Wage differentials can also be examined through social constructs such as gender and race. Economic literature points to the impact of socio-demographic and academic characteristics on

both college major choice and wage differentials across time (Melguizo et al., 2011; Olitsky, 2013). Zhang (2008) found that while college major was the most predictive factor in determining wage differentials across time, large racial disparities were found in pay over time among college graduates, suggesting a contributing effect of both socio-economic and academic factors in determining wage differentials. These data are supported by numerous other studies that have found racial disparities in earnings, particularly in STEM fields, with Black and Hispanic earnings being significantly lower than those of White and Asian STEM workers (Landivar, 2013; Lysenko & Wang, 2020).

Studies have also found major-occupation congruence (working in the same area as your certification and credentials) to be positively associated with higher wage differentials, specifically in skill-requiring majors such as engineering (Malamud, 2011). However, recent findings from the U.S. Census Bureau suggest that a significant portion of STEM graduates are employed in non-STEM occupations. According to the Census Bureau's American Community Survey, over half (62%) of STEM graduates in 2019 from ages 25-64 were employed in non-stem occupations such as law, education, social work, and accounting, with less than a third of STEM-educated graduates (28%) working in a STEM occupation (Cheeseman Day & Martinez, 2021). These percentages are even lower for minority students. Estimates indicate that only 9.3% of STEM undergraduates from Black or African American students and 10.7% of Hispanic undergraduates work in STEM occupations, compared to 12.6% of White students (U.S. Census Bureau, 2019). These data provide further evidence of the disparities in STEM employment across races and highlight the continuous barriers and challenges faced by minority students to and through their STEM educational trajectory and into the STEM workforce. These findings also support the notion of promoting upward economic mobility for socio-economically disadvantaged minority students entering STEM occupations, as an extensive body of research demonstrates that STEM graduates who go on to work in STEM fields make significantly higher earnings compared to those who do not (Carnevale et al., 2011; Cheeseman Day & Martinez, 2021).

One of the national initiatives used to combat racial disparities in STEM degree attainment is STEM intervention programs. Designed to boost academic preparation and provide financial assistance to URM students, studies have found strong associations between program participation and persistence in the STEM field (Carpi et al., 2017; Jackson & Winfield, 2014; Lee & Harmon, 2013). Specifically, STEM intervention programs that focus on academic preparation in math play a crucial role in boosting the math skills of disadvantaged URM students, many of whom did not receive adequate pre-college math preparation (Chang et al., 2014; Lisberg & Woods, 2018). Research suggests significant positive associations between early interventions in math and academic outcomes, particularly for disadvantaged students (Cortes, Goodman & Nomi, 2015). Furthermore, collective studies demonstrate the positive impact of academic preparation in math on labor market outcomes (Dolton & Vignoles, 2002;

Goodman, 2012; Rose & Betts, 2004). Despite this evidence, few studies examine the role of such programs on the earning outcomes of minority students after graduation. Several components of STEM intervention programs contribute to higher wage earnings across time, specifically social and academic engagement and academic achievement. Literature highlights academic achievement as a critical factor in both STEM college major choice and increased wage earnings, particularly among under-represented minority students (Melguizo et al., 2011; Thomas, 2008).

Additionally, student engagement in different aspects of the college environment is significantly associated with higher earning benefits in the labor market (Hu & Wolniak, 2010). Although these findings provide a broad outline of features of intervention programs that are significantly associated with wage premiums, there is an increased need to understand the role of such interventions in the economy and society. In particular, our study addresses the following research questions:

- 1) Descriptively, to what extent have H-LSAMP scholars who graduated with STEM degrees, pursued post-graduate higher education, and entered STEM-related occupations?
- 2) To what extent does participation in the H-LSAMP program associate with higher wages compared to non-participants of the program?

## **Study Significance**

This study adds to the existing body of literature in several distinct ways. Primarily, this study offers a unique perspective on the mechanisms and approaches through which current opportunities and interventions can expand the wage earnings of under-represented minority students. In addition, by utilizing the rich repository of data available through the UH-ERC, this study was able to track H-LSAMP student outcomes from university into the Texas workforce. This expansive availability of data enabled this study to identify factors early in a student's education that could influence earning outcomes, filling the gap in the current research literature involving wage trajectories of under-represented minority students in STEM careers as impacted by STEM intervention programs. On a local level, these findings could provide the alliance with empirically based recommendations on program components targeted to improve wage earnings among high-risk minority students. In addition, these results could assist in better resource allocation towards program initiatives and components most beneficial to URM students.

## **Theoretical/Conceptual Framework**

This study draws upon Paulsen's (2001) human capital framework as well as Perna's (2004) expanded econometric framework that considers racial and ethnic disparities in educational attainment. Human capital perspectives center around the value of higher education and

curriculum in developing skills that increase student productivity and, consequently, lead to increased monetary and non-monetary rewards (Paulsen, 2001; Rose & Betts, 2004). Perna (2004) created an expanded econometric framework that considers social and cultural capital measures that may influence student preferences, enrollment decisions, and outcomes (Paulsen & St. John, 2002; Perna, 2004). Despite being largely ignored in formative econometric frameworks, scholars agree that including social and cultural capital measures is beneficial for examining racial disparities in educational attainment. Prior research studies have highlighted the role of social and cultural capital as valuable resources that enhance upward mobility and productivity (Coleman, 1998; Morrow, 1999). From a human capital perspective, STEM enrichment programs focus on building the academic preparation, skills, and knowledge that will enable URM students to graduate successfully and enter STEM careers. Studies also show that the social engagement and academic support provided as part of the STEM enrichment program experience contribute to more successful enrollment and labor outcomes (Hu & Wolniak, 2010). Drawing on Perna's (2004) framework, the support offered through such programs in the form of faculty or peer mentorship and advising, as well as informal interactions with peers, can have significant positive effects on building students' social capital. Guided by elements of both frameworks, this study aims to examine the role of both ascribed (socio-demographic) and achieved characteristics related to intervention programs designed to increase URM students' academic preparation, success, and wage outcomes in STEM fields.

## Data Source

This study analyzes data available through the University of Houston's Education Research Center, which contains essential student-level longitudinal information from the Texas Education Agency (TEA), the Texas Higher Education Coordinating Board (THECB), and the Texas Workforce Commission (TWC). Data provided through the ERC enables Texas students to be tracked across time from high school, higher education, and into the workforce. The data sample analyzed consists of college graduates from the H-LSAMP program from 2004-2019 ( $n = 1,828$ ), as well as graduate degree recipients of the program ( $n = 322$ ). In addition, matched records of non-participants of the program were analyzed. The H-LSAMP consortium includes five Texas higher education institutions that dedicate active efforts to recruit, academically prepare and graduate students, particularly those from under-represented backgrounds, to successful matriculation into the STEM pipeline.

## Research Methods

The analysis for this study relied on both descriptive and inferential statistics. Valletta's (2018) Wage Earning's Function was used to examine yearly wage outcomes of H-LSAMP participants and matched non-participants of the program. The analysis was conducted in two stages; first,

propensity score matching techniques were used to account for unobserved characteristics and self-selection bias associated with program participation (Rosenbaum & Ruben, 1983). One of the major advantages of propensity score matching techniques is the ability to match participants on a series of baseline covariates, creating a control group with similar characteristics comparable to our treatment group of interest. In the present study, treatment represents participation in the H-LSAMP program. This first step of the analysis included matching students based on race, age, and STEM vs. non-STEM degree field. This process created a matched group of non-participants of the HLSAMP program with similar baseline characteristics as program participants, allowing for the reduction of bias in participation effects throughout the second stage of the analysis. The second stage of the analysis involved linear regression techniques to estimate program participation effects on wage earnings after accounting for estimated propensity scores. Conventional regression models do not properly control for selection bias, as students who enter the program may differ on several background characteristics. Hence, the effects of these background variables undermine causal inference (Winship & Morgan, 1999). To examine the wage benefits associated with H-LSAMP program participation, this study employed the standard log estimates equation used by Valletta (2018):

$$\ln W_i = X_i\beta + S_i\Gamma + \varepsilon_i$$

Where  $W$  represents yearly wage earnings,  $X$  represents the estimated propensity scores used to match similar students, as well as a dummy variable indicating H-LSAMP program participation.  $S$  represents a vector of completion characteristics discussed in the variable section, allowing for the control of education and workforce variables that may contribute to wage differences among students, and  $\varepsilon$  represents the error term. The resulting equation enabled this study to examine the wage premium associated with H-LSAMP participation after controlling for socio-demographic and pre-college characteristics.

## Variables

### Dependent Variable

The dependent variable of interest was the natural log of yearly earnings. Wage earnings reported every quarter were converted to annual estimates. Texas Workforce Commission data from the UH-ERC was merged with higher education data with an identifier for HLSAMP participants. Merging both datasets allowed for the longitudinal tracking of HLSAMP and non-LSAMP participants from college and into the workforce and any associated differences in long-term wage earnings.

## Control Variables

To control for student background characteristics, the propensity score model covariates included the socio-demographic variables of gender, age, race, and STEM vs. non-STEM major enrollment based on the supporting evidence of ascribed socio-demographic and socio-economic characteristics on economic outcomes (Hu & Wolniak, 2010; Thomas; 2000; Xu, 2013). Table 1 presents coding schemes of control variables used for propensity score matching analysis.

**TABLE 1.** Control variables coding scheme

| <b>Variable</b>   | <b>Coding</b>  |
|-------------------|--|
| Age               | Continuous   |
| Race              | 0 - White<br>1 - Black<br>2 - Asian<br>3 - Hispanic<br>4 - Other |
| STEM degree field | 0 – non-STEM<br>1 - STEM   |

## Independent Variables

In addition to the control variables used to match students, variables included in the linear regression model included the student's field of study, estimated propensity scores, participation in the HLSAMP program, major-field congruence (dummy-variable), occupation industry, and years of workforce experience. Given that the workforce data available is limited to occupational codes represented by the Standard Industrial Classification (SIC) codes, industry classifications, rather than specific occupations, could only be represented in this analysis. Table 2 presents coding schemes of variables included in the logistic regression analysis. Particularly relevant to this study, non-STEM fields of study are defined as any not categorized among natural science, engineering, and computer science majors. Occupation is similarly defined as STEM or non-STEM based on the Texas Workforce Commission classification. Major-occupation congruence indicates where an individual worked in a profession aligned with or different from their undergraduate degree (e.g., a STEM major in a STEM field would represent major-occupation congruence).

**TABLE 2.** Coding schemes: Independent variables

| <b>Variable</b>             | <b>Coding</b>       |
|-----------------------------|---------------------|
| Estimated Propensity Scores | Continuous          |
| Program Participation       | 0 – non-participant |

|                               |   |
|-------------------------------|---|
| Field of Study                | 1 - participant<br>0 – non-STEM<br>1 – Natural Science & Mathematics<br>2 - Engineering<br>3 – Computer Science |
| Occupation                    | 0 – non-STEM<br>1 - STEM  |
| Major-Occupation Congruence   | 0 – non-congruent<br>1 - congruent  |
| Years of Workforce Experience | Continuous  |

## Results

### Descriptive Outcomes

Propensity score matching was conducted using the program match, resulting in a matched sample of 3,765 students, including 1,780 treatment and 1,985 control participants. Students whose records did not match the workforce data were excluded from the analysis. Table 3 presents descriptive results of the matched group of HLSAMP participants and non-participants.

**TABLE 3.** Descriptive characteristics: Matched sample

| Variable           | Control       | Treat       |
|--------------------|---------------|-------------|
|                    | N<br>%        | N<br>%      |
| <b><i>Race</i></b> |               |             |
| White              | 167<br>9.2    | 178<br>9.0  |
| <i>Black</i>       | 525<br>29.0   | 546<br>27.6 |
| <i>Asian</i>       | 463<br>25.6   | 473<br>23.9 |
| <i>Hispanic</i>    | 430<br>23.8   | 432<br>21.8 |
| <i>Other</i>       | 225<br>12.4   | 352<br>17.8 |
| <b>Gender</b>      |               |             |
| <i>Male</i>        | 974<br>53.8   | 836<br>46.2 |
| <i>Female</i>      | 1,070<br>54.0 | 911<br>46.0 |

|  |      |       |
|--|------|-------|
| <b>STEM degree</b>                       |      |       |
| <i>Non-STEM</i>                          | 964  | 918   |
|  | 53.9 | 46.4  |
| <i>STEM</i>                              | 824  | 1,059 |
|  | 46.1 | 53.6  |
| <b>Degree Field</b>                      |      |       |
| <i>Natural Science &amp; Mathematics</i> | 858  | 930   |
|  | 47.4 | 47.0  |
| <i>Engineering</i>                       | 642  | 696   |
|  | 35.5 | 35.1  |
| <i>Computer Science</i>                  | 118  | 118   |
|  | 6.5  | 6.0   |
| <i>Other/non-STEM</i>                    | 192  | 237   |
|  | 10.6 | 12.0  |
| <b>Occupation</b>                        |      |       |
| <i>Stem-related</i>                      | 804  | 1,067 |
|  | 45.1 | 53.7  |
| <i>Non-stem related</i>                  | 979  | 921   |
|  | 54.9 | 46.3  |
| <b>Major-Occupation Congruence</b>       |      |       |
| <i>Non-congruent</i>                     | 908  | 880   |
|  | 50.8 | 49.2  |
| <i>Congruent</i>                         | 872  | 1,105 |
|  | 44.1 | 55.8  |

Table 4 presents the regression results examining the effect of H-LSAMP program participation on log wages using the estimated propensity scores as a control variable. Results indicate that H-LSAMP program participation negatively predicted higher wages among students from all STEM and non-STEM fields. At the same time, STEM-related occupations, as well as years of workforce experience, were significant predictors of higher wages among all students. Results also indicated that students majoring in NSM, Engineering, and Computer Science fields had significantly higher wages than those majoring in non-STEM majors. In addition, major-occupation congruence was not associated with higher wage differentials among students in the treatment and control groups.

**TABLE 4.** OLS regression results

| Variables | 95% C. I for Exp |           |
|-----------|------------------|-----------|
|           | $\beta$          | $\beta$ ) |

|   |                       |         |        |
|---|-----------------------|---------|--------|
| <b>Estimated Propensity Scores</b>                            | 0.04                  | -0.029  | 0.11   |
| <b>Treatment</b> (Reference: Non-treated)                     | -0.009**              | -0.014  | -0.005 |
| <b>Field</b> (Reference: Other/non-STEM)                      |                       |         |        |
| NSM   | 0.017**               | 0.010   | 0.023  |
| Engineering   | 0.025**               | 0.017   | 0.032  |
| Computer Science  | 0.012**               | 0.003   | 0.021  |
| <b>Major-Occupation Congruence</b> (Reference: Non-Congruent) |                       |         |        |
| Congruent   | 0.0046                | -0.0016 | 0.011  |
| <b>Occupation</b> (Reference: non-STEM related)               |                       |         |        |
| STEM-related  | 0.018**               | 0.011   | 0.024  |
| Years of Workforce Experience                                 | 0.0035**              | 0.0031  | 0.0039 |
| <b>Model Summary</b>  |                       |         |        |
|   | N                     | 3,765   |        |
|   | Pseudo R <sup>2</sup> | 0.1143  |        |
|   | F(8,3,762)            | 88.28   |        |

\*p<0.05

\*\*p<0.005

Tables 5 and 6 demonstrate Ordinal Logistic Regression results across STEM fields, including NSM, Engineering, and Computer Science. Similar to OLS regression results across students from all fields of undergraduate study, H-LSAMP program participation was a negative predictor of higher wage differentials among students in all three STEM fields. However, major-occupation congruence was found to be a significant predictor of higher wage differentials for each category of the STEM field, as well as years of workforce experience.

**TABLE 5.** OLS regression: NSM majors

| Variables   | $\beta$               | 95% C. I for Exp $\beta$ ) |         |
|---|-----------------------|----------------------------|---------|
| <b>Estimated Propensity Scores</b>                            | 0.095*                | 0.021                      | 0.17    |
| <b>Treatment</b> (Reference: Non-Treated)                     | -0.010**              | -0.017                     | -0.0036 |
| <b>Major-Occupation Congruence</b> (Reference: Non-Congruent) |                       |                            |         |
| Congruent   | 0.027**               | 0.020                      | 0.035   |
| Years of Workforce Experience                                 | 0.0032**              | 0.0027                     | 0.0038  |
| <b>Model Summary</b>  |                       |                            |         |
|   | N                     | 1,775                      |         |
|   | Pseudo R <sup>2</sup> | 0.1080                     |         |
|   | F(4,1770)             | 64.63                      |         |

\*p<0.05

\*\*p<0.005

**TABLE 6.** OLS regression results: Engineering majors

| Variables   |         |                            |        |
|---|---------|----------------------------|--------|
|   | $\beta$ | 95% C. I for Exp $\beta$ ) |        |
| <b>Estimated Propensity Scores</b>                            | -0.135  | -0.314                     | 0.045  |
| <b>Treatment</b> (Reference: Non-Treated)                     | -0.011* | -0.020                     | -0.002 |
| <b>Major-Occupation Congruence</b> (Reference: Non-Congruent) |         |                            |        |
| Congruent   | 0.020** | 0.010                      | 0.031  |
| Years of Workforce Experience                                 | 0.004** | 0.0034                     | 0.0051 |
| <b>Model Summary</b>  |         |                            |        |
| N   |         | 1,328                      |        |
| Pseudo R <sup>2</sup>   |         | 0.1021                     |        |
| F(4,1323)   |         | 57.44                      |        |

\*p&lt;0.05

\*p&lt;0.005

**Table 8***OLS Regression Results: Computer Science Majors*

| Variables   |          |                            |          |
|---|----------|----------------------------|----------|
|   | $\beta$  | 95% C. I for Exp $\beta$ ) |          |
| <b>Estimated Propensity Scores</b>                            | 0.104    | 0.31                       | 0.51     |
| <b>Treatment</b> (Reference: Treated)                         | -0.014*  | -0.028                     | -0.00043 |
| <b>Major-Occupation Congruence</b> (Reference: Non-Congruent) |          |                            |          |
| Congruent   | 0.0049** | 0.010                      | 0.020    |
| Years of Workforce Experience                                 | 0.004**  | 0.0024                     | 0.0048   |
| <b>Model Summary</b>  |          |                            |          |
| N   |          | 234                        |          |
| Pseudo R <sup>2</sup>   |          | 0.1341                     |          |
| F(4,229)  |          | 12.01                      |          |

\*p&lt;0.05

\*p&lt;0.005

**Limitations**

There are some limitations to the data analysis that warrant discussion. Firstly, our propensity score analysis matched students solely on race, age, gender, and STEM vs. non-STEM degree fields. Given that HLSAMP program participants are recruited from low-performing high schools, the inability to match students on socio-economic status, quality of high school, and pre-college academic performance limit the analysis results. To that end, interpreting the results of program participation effects on program participants should be done with caution, as our matching process did not include variables that could potentially affect participation effects, given the lack of data availability. Secondly, the results of this study apply to a single intervention program applicable to only Texas-based students. Despite the program size, which includes five partner institutions, our results do not necessarily apply to students from other states and regions. Nevertheless, findings from this study do provide an essential understanding of program participation effects on wages that could be used as a useful guide for other STEM intervention programs across the nation.

## Discussion

Findings from this study corroborate prior research indicating that majoring in STEM fields contributes to higher wage differentials for STEM undergraduates compared to other disciplines (Blackburn, 2004; Carnevale et al., 2011; Cheeseman Day & Martinez, 2021). Results also support prior findings of the significance of major-occupation congruence on higher wage earnings, particularly for highly technical and skill-requiring majors (Malamud, 2011). While the general OLS regression model did not show any significant association between major-occupation congruence and higher wage differentials across all majors, this variable was a significant predictor for students majoring in NSM, Computer Science, and Engineering. These findings support an extensive body of research highlighting the importance of college major choice on future labor market earnings, specifically for STEM major choices (Melguizo et al., 2011; Thomas, 2008)

However, the results of this study leave more to be uncovered on the impact of socio-economic and racial disparities on labor market earnings. Despite findings that STEM major choice and employment in a STEM field lead to higher wage differentials, participating in a STEM-enriched intervention program, according to our findings, is negatively associated with higher wage differentials. Despite the negative association, the small size of the coefficients indicates a relatively weak negative relationship between program participation and wage differentials. Given that a large portion of STEM intervention programs, including the program studied in this analysis, are targeted towards under-represented minorities from low socio-economic backgrounds, this finding brings to light the large racial and socio-economic disparities in STEM labor market earnings that are persistent despite the successful graduation of minority students participating in these programs. Program participants are more likely to come from relatively

disadvantaged economic backgrounds and are less likely to have adequate parental financial support (Ghazzawi et al., 2021; Kao & Thompson, 2003). These socio-economic factors, as well as the inadequate pre-college preparation of URM program participants, contribute to racial disparities in pay, particularly in STEM occupations (Chen & Soldner, 2013; Zhang, 2008). These results suggest that socio-economic and pre-college factors extend beyond college education and considerably influence the wage earnings of URM students in STEM (Zhang, 2008).

## **Directions for Policy and Practice**

Given the findings of this study and other studies that indicate racial disparities in wages, it is clear that colleges and universities must shift their focus from graduating a large number of URM students in STEM to ensuring that URM students graduate with the same level of human capital as their White counterparts (Broyles & Fenner, 2010; Zhang, 2008). Stronger career preparedness, internship opportunities, and networking events are all as crucial to URM student success as graduating with a STEM degree. For these reasons, realigning intervention program components and goals to focus on equipping URM students with workforce and career preparedness is a significant step in improving the human capital of URM students as they enter the STEM workforce. In addition, the results of this study also point to the need for policymakers to address racial inequities in pay across the nation, particularly in STEM fields. It also would behoove student advisors to counsel students about local employment opportunities available in their chosen field of study early in their academic career, as many minority students are reluctant to accept jobs far from home (Estrada et al., 2018). This can lead to the selection of a non-STEM-related job after college if employment matching the degree is unavailable locally.

Beyond programs and policies centered in academic institutions, work is also needed to confront continuing disparities in opportunities from the job application and selection process to opportunities for advancement and leadership roles and the general climate of the workplace. Barriers centered on inappropriate sorting criteria and continuous microaggressions based on race and gender impact whether individuals are hired into STEM careers and whether they choose to stay in the long term. Minoritized groups suffer additional stressors in the workplace resulting from perceived and actual racism that impact self-confidence, self-image, and upward mobility (Yosso et al., 2009).

## **Directions for Future Research**

To better understand the socio-economic and pre-college factors contributing to wage disparities, further research is needed to investigate the role of financial aid and pre-college ability in more detail. Since this data was not available to examine in the current study, this level of inquiry

could not be included. Furthermore, future work should consider the role of different intervention program components, such as the amount of scholarship awards and internship and mentorship opportunities that contribute to higher wage differentials over time. Such analysis will yield program administrators and practitioners valuable recommendations that could improve and tailor program components to benefit the labor market outcomes of URM students. Finally, a more detailed inquiry on the impact of specific STEM occupations on wage differentials, specifically for URM students, would be a significant contribution to the literature on the contributing effect of STEM occupations and fields on labor market earnings for this particular population of students (Malamud, 2011).

## References

- Allen-Ramdial, S. A. A., & Campbell, A. G. (2014). Reimagining the pipeline: Advancing STEM diversity, persistence, and success. *BioScience*, 64(7), 612-618. Doi: 10.1093/biosci/biu076
- Blackburn, M. L. (2004). The role of test scores in explaining race and gender differences in wages. *Economics of Education Review*, 23(6), 555-576. Doi: 10.1016/j.econedurev.2004.04.005
- Broyles, P., & Fenner, W. (2010). Race, human capital, and wage discrimination in STEM professions in the United States. *International Journal of Sociology and Social Policy*, 30(5/6), 251–266. <https://doi.org/10.1108/01443331011054226>
- Grogger, J., & Eide, E. (1995). Changes in college skills and the rise in the college wage premium. *Journal of Human Resources*, 280-310. Doi: 10.2307/146120
- Carnevale, A. P., Cheah, B., & Rose, S. J. (2011). *The College pays off*. [White paper]. Georgetown University Center on Education and the Workforce. Retrieved from: <https://vtechworks.lib.vt.edu/bitstream/handle/10919/83051/TheCollegePayOff.pdf?sequence=1>
- Carpi, A., Ronan, D. M., Falconer, H. M., & Lents, N. H. (2017). Cultivating minority scientists: Undergraduate research increases self-efficacy and career ambitions for underrepresented students in STEM. *Journal of Research in Science Teaching*, 54(2), 169-194. Doi: 10.1002/tea.21341
- Chang, M. J., Sharkness, J., Hurtado, S., & Newman, C. B. (2014). What matters in college for retaining aspiring scientists and engineers from underrepresented racial groups. *Journal of Research in Science Teaching*, 51(5), 555-580. Doi: 10.1002/tea.21146
- Cheeseman, J., & Martinez, A. (2021). *STEM majors earned more than other STEM workers*. America counts: Stories Behind the Numbers. <https://www.census.gov/library/stories/2021/06/does-majoring-in-stem-lead-to-stem-job-after-graduation.html>
- Chen, X., & Soldner, M. (2013). *STEM attrition: College students' paths into and out of STEM fields* (NCES 2014-001). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. <https://nces.ed.gov/pubs2014/2014001rev.pdf>

- Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, 94, S95-S120. Doi: 10.1086/228943
- Cortes, K. E., Goodman, J. S., & Nomi, T. (2015). Intensive math instruction and educational attainment long-run impacts of double-dose algebra. *Journal of Human Resources*, 50(1), 108-158. Doi: 10.3368/jhr.50.1.108
- Dolton, P. J., & Vignoles, A. (2002). Is a broader curriculum better? *Economics of Education Review*, 21(5), 415-429. Doi: 10.1016/S0272-7757(01)00046-2
- Goodman, J. S. (2012). *The labor of division: Returns to compulsory math coursework*. [White paper]. HKS Faculty Research Working Paper Series RWP12-032, John F. Kennedy School of Government, Harvard University. <https://dash.harvard.edu/handle/1/9403178>
- Eagan Jr, M. K., Hurtado, S., Chang, M. J., Garcia, G. A., Herrera, F. A., & Garibay, J. C. (2013). Making a difference in science education: the impact of undergraduate research programs. *American Educational Research Journal*, 50(4), 683-713. Doi: doi.org/10.3102/0002831213482038
- Estrada, M., Hernandez, P. R., & Schultz, P. W. (2018). A longitudinal study of how quality mentorship and research experience integrate underrepresented minorities into STEM careers. *CBE—Life Sciences Education*, 17(1), ar9, 1-13. Doi: 10.1187/cbe.17-04-0066
- Foltz, L. G., Gannon, S., & Kirschmann, S. L. (2014). Factors that contribute to the persistence of minority students in STEM Fields. *Planning for Higher Education*, 42(4), 1-13.
- Ghazzawi, D., Pattison, D., & Horn, C. (2021). Persistence of Underrepresented Minorities in STEM Fields: Are Summer Bridge Programs Sufficient? *In Frontiers in Education*, (6), Article 630529. doi: 10.3389/feduc.2021.630529
- Ghazzawi, D., Pattison, D. L., Horn, C., Hardy, J. and Brown, B. (2022b). Impact of an intensive multi-disciplinary STEM enrichment program on underrepresented minority student success. *Journal of Applied Research in Higher Education*, 14 (2), 660-678. <https://doi.org/10.1108/JARHE-12-2020-0452>
- Ghazzawi, D., Pattison, D., Horn, C., Wilson, B. (2022a). Houston-Louis Stokes Alliance for Minority Participation: Findings from 17 years of a multi-institutional consortium focused on building minority student success in STEM. *Electronic Journal for Research in Science & Mathematics Education*, 26(3), 1-18.

- Hu, S., & Wolyniak, G. C. (2010). Initial evidence on the influence of college student engagement on early career earnings. *Research in Higher Education, 51*(8), 750-766. Doi: 10.1007/s11162-010-9176-1
- Jackson, K. M., & Winfield, L. L. (2014). Realigning the crooked room: Spelman claims a space for African American women in STEM. *Peer Review: Emerging Trends and Key Debates in Undergraduate Education, 16*(2), 9.
- Kao, G., & Thompson, J. S. (2003). Racial and ethnic stratification in educational achievement and attainment. *Annual Review of Sociology, 29*(1), 417-442. Doi: 10.1146/annurev.soc.29.010202.100019
- Landivar, L. C. (2013). Disparities in STEM employment by sex, race, and Hispanic origin. *Education Review, 29*(6), 911-922.
- Leath, S., & Chavous, T. (2018). Black women's experiences of campus racial climate and stigma at predominantly white institutions: Insights from a comparative and within-group approach for STEM and non-STEM majors. *The Journal of Negro Education, 87*(2), 125-139. Retrieved from <https://www.jstor.org/stable/10.7709/jnegroeducation.87.2.0125>
- Lee, D. M., & Harmon, K. (2013). The Meyerhoff Scholars Program: Changing Minds, Transforming a Campus. *Metropolitan Universities, 24*(2), 55-70. Retrieved from <https://journals.iupui.edu/index.php/muj/article/view/20547>
- Lisberg, A., & Woods, B. (2018). Mentorship, mindset and learning strategies: an integrative approach to increasing underrepresented minority student retention in a STEM undergraduate program. *Journal of STEM Education, 19*(3). Retrieved from <https://www.learntechlib.org/p/184625/>
- Lysenko, T., & Wang, Q. (2020). Race/Ethnicity, Gender, and Earnings of Early Career STEM Graduates in the U.S. *Geographical Review, 110*(4), 457-484. Doi: 10.1080/00167428.2019.1708742
- Malamud, O. (2011). Discovering one's talent: Learning from academic specialization. *ILR Review, 64*(2), 375-405. Doi: 10.1177/001979391106400209
- McGee, E. O. (2020). Interrogating structural racism in STEM higher education. *Educational Researcher, 49*(9), 633-644. Doi: 10.3102/0013189X20972718

- Melguizo, T., Kienzl, G. S., & Alfonso, M. (2011). Comparing the educational attainment of community college transfer students and four-year college rising juniors using propensity score matching methods. *The Journal of Higher Education*, 82(3), 265-291. Doi: 10.1080/00221546.2011.11777202
- Morrow, V. (1999). Conceptualizing social capital in relation to the well-being of children and young people: a critical review. *The Sociological Review*, 47(4), 744-765. Doi: 10.1111/1467-954X.00194
- National Center for Science and Engineering Statistics. (2019). *Women, minorities, and persons with disabilities in science and engineering*. (NSF 21-321). National Science Foundation. <https://nces.nsf.gov/pubs/nsf19304/data>
- National Center for Science and Engineering Statistics. (2018). *Science and engineering degrees, by race and ethnicity of recipients*. National Science Foundation. <https://www.nsf.gov/statistics/degreerecipients/>.
- Olitsky, N. H. (2014). How do academic achievement and gender affect the earnings of STEM majors? A propensity score matching approach. *Research in Higher Education*, 55(3), 245-271. Retrieved from <https://www.jstor.org/stable/24571759>
- Paulsen, M. B. (2001). The economics of human capital and investment in higher education. In Paulsen, M. B., & Smart, J. C. (Eds.) *The finance of higher education: Theory, research, policy, and practice* (pp. 55-94). Agathon Press.
- Paulsen, M. B., & John, E. P. S. (2002). Social class and college costs: Examining the financial nexus between college choice and persistence. *The Journal of Higher Education*, 73(2), 189-236. Doi: 10.1080/00221546.2002.11777141
- Perna, L. W. (2004). Understanding the decision to enroll in graduate school: Sex and racial/ethnic group differences. *The Journal of Higher Education*, 75(5), 487-527. Doi: 10.1080/00221546.2004.11772335
- Rose, H., & Betts, J. R. (2004). The effect of high school courses on earnings. *Review of Economics and Statistics*, 86(2), 497-513. Doi: 10.1162/003465304323031076
- Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41-55. Doi: 10.1093/biomet/70.1.41

- Tobias, J. L., & Li, M. (2003). A finite-sample hierarchical analysis of wage variation across public high schools: evidence from the NLSY and high school and beyond. *Journal of Applied Econometrics*, 18(3), 315-336. Doi: 10.1002/jae.696
- Thomas, S. L. (2000). Deferred costs and economic returns to college major, quality, and performance. *Research in Higher Education*, 41(3), 281-313. Doi: 10.1023/A:1007003510102
- Treisman, U. (1992). Studying students studying calculus: A look at the lives of minority mathematics students in college. *The College Mathematics Journal*, 23(5), 362-372. Doi: 10.1080/07468342.1992.11973486
- Turk-Bicakci, L., & Berger, A. (2014). Leaving STEM: STEM Ph. D. Holders in Non-STEM Careers. Issue Brief. *American Institutes for Research*. Retrieved from <https://eric.ed.gov/?id=ED545309>
- Valletta, R. G. (2018). Recent flattening in the higher education wage premium: Polarization, skill downgrading, or both? In Hulten, C. R., & Ramey, V. A. (Eds.), *Education, skills, and technical change: Implications for future US GDP growth* (pp. 313-342). University of Chicago Press. Doi: 10.7208/9780226567945-010
- Valletta, Robert G.. "9. Recent Flattening in the Higher Education Wage Premium Polarization, Skill Downgrading, or Both?". *Education, Skills, and Technical Change: Implications for Future US GDP Growth*, edited by Charles R. Hulten and Valerie A. Ramey, Chicago: University of Chicago Press, 2018, pp. 313-354. <https://doi.org/10.7208/9780226567945-010>
- Wimpelberg, R. (2008). The Greater Houston P-16+ Council: Systemic pathways to birth-to-career access and success. *Metropolitan Universities*. 19(4), 18-22.
- Winship, C. & Morgan, L. (2019). The estimation of causal effects from observational data. *Annual Review of Sociology*, 25(1), 659-706. Doi: 10.1146/annurev.soc.25.1.659
- Xu, Y. J. (2013). Career outcomes of STEM and non-STEM college graduates: Persistence in majored-field and influential factors in career choices. *Research in Higher Education*, 54(3), 349-382. Retrieved from <https://www.jstor.org/stable/23471103>
- U.S. Census Bureau. (2019). 2019 *American Community Survey, 1-year estimates*. U.S. Department of Commerce. Retrieved from [www.census.gov/programs-surveys/acs](http://www.census.gov/programs-surveys/acs)

Yosso, T. J., Smith, W. A., Ceja, M., Solórzano, D. G., (2009). Critical Race Theory, racial microaggressions, and campus racial climate for Latina/o undergraduates. *Harvard Educational Review*. 79(4), 659-691.

Zambrana, R. E., Harvey Wingfield, A., Lapeyrouse, L. M., Dávila, B. A., Hoagland, T. L., & Valdez, R. B. (2017). Blatant, subtle, and insidious: URM faculty perceptions of discriminatory practices in predominantly White institutions. *Sociological Inquiry*, 87(2), 207-232. Doi: 10.1111/soin.12147

Zhang, L. (2008). Gender and racial gaps in earnings among recent college graduates. *The Review of Higher Education*, 32(1), 51-72. Doi: 10.1353/rhe.0.0035