

Essays on educational choices, peer effects, and diversity in higher education

by

Seungmin Mike Yang

B.A., Kansas State University, 2020

M.A., Kansas State University, 2025

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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the  
requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Economics  
College of Arts and Sciences

KANSAS STATE UNIVERSITY  
Manhattan, Kansas

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# Abstract

This dissertation studies how students' outcomes depend not only on who they are or what they choose individually, but also on the academic environments around them. The chapters focus on two settings: how students combine undergraduate majors, and how students are affected by the composition of their doctoral cohorts. Across these settings, the dissertation asks how academic breadth, peer composition, and diversity shape educational and labor-market outcomes.

Chapter 1, joint work with my advisor Dr. Valerie Bostwick, studies double majoring. The chapter asks whether having two undergraduate majors is associated with higher wages, and whether the answer depends on the relationship between the two fields. A second major may be valuable when it complements the first major, but it may be less valuable if it pulls students away from deeper specialization. Using ACS data, the chapter shows that the returns to double majoring differ by field combination and by gender.

Chapter 2 examines doctoral cohorts and focuses on changes in the share of international students within an entering cohort. It asks how doctoral outcomes change as the international-student share of a cohort increases. Specifically, the chapter studies whether a higher share of international peers is associated with students' persistence, time to degree, and degree completion, and whether these relationships differ across fields and cohort environments.

Chapter 3 also studies doctoral cohorts, but focuses on broader forms of diversity. It examines gender, racial/ethnic, and linguistic diversity within doctoral entering cohorts. The chapter asks whether these forms of diversity are related to doctoral students' progress and completion, and whether the relationships differ depending on the type of diversity and the initial composition of the cohort.

Together, the three chapters show that composition matters, but not in a simple one-directional way. A second major, an international peer group, or a diverse cohort can have different implications depending on the field, the type of composition, and the environment in which students are embedded. The dissertation therefore highlights the importance of looking beyond individual students and studying the academic contexts in which educational choices and outcomes take shape.

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Major Professor  
Valerie Bostwick

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# Contents

|                                                                 |     |
|-----------------------------------------------------------------|-----|
| List of Figures . . . . .                                       | xi  |
| List of Tables . . . . .                                        | xii |
| Acknowledgments . . . . .                                       | xv  |
| 1 The Double Major Dilemma . . . . .                            | 1   |
| 1.1 Introduction . . . . .                                      | 1   |
| 1.2 Related Literature . . . . .                                | 5   |
| 1.2.1 College Majors and Field-Specific Human Capital . . . . . | 5   |
| 1.2.2 The Returns to Double Majoring . . . . .                  | 6   |
| 1.2.3 Occupational Match and Gender . . . . .                   | 7   |
| 1.3 Conceptual Framework . . . . .                              | 8   |
| 1.4 Data . . . . .                                              | 9   |
| 1.5 Empirical Strategy . . . . .                                | 14  |
| 1.6 Results . . . . .                                           | 17  |
| 1.6.1 Average Returns to Double Majoring . . . . .              | 17  |
| 1.6.2 Local and Global Double Majors . . . . .                  | 21  |
| 1.6.3 Heterogeneity by Gender . . . . .                         | 22  |
| 1.7 Potential Mechanisms . . . . .                              | 24  |
| 1.7.1 Graduate Education . . . . .                              | 24  |
| 1.7.2 STEM Occupations . . . . .                                | 29  |
| 1.7.3 Occupation Match . . . . .                                | 31  |
| 1.8 Major Ordering . . . . .                                    | 34  |

|       |                                                                   |     |
|-------|-------------------------------------------------------------------|-----|
| 1.9   | Conclusion . . . . .                                              | 38  |
| 2     | International Peer Effects in Doctoral Education . . . . .        | 40  |
| 2.1   | Introduction . . . . .                                            | 40  |
| 2.2   | Related Literature . . . . .                                      | 43  |
| 2.3   | Conceptual Framework . . . . .                                    | 45  |
| 2.4   | Data . . . . .                                                    | 48  |
| 2.5   | Empirical Strategy . . . . .                                      | 52  |
| 2.5.1 | Identification Assumption . . . . .                               | 53  |
| 2.5.2 | Monte Carlo Simulation . . . . .                                  | 54  |
| 2.6   | Results . . . . .                                                 | 56  |
| 2.6.1 | Heterogeneity by Field of Study . . . . .                         | 57  |
| 2.6.2 | Heterogeneity by Program Size . . . . .                           | 61  |
| 2.6.3 | Nonlinearity Analysis . . . . .                                   | 64  |
| 2.6.4 | Potential Mechanisms . . . . .                                    | 69  |
| 2.7   | Discussion and Conclusion . . . . .                               | 78  |
| 3     | Diversity in Ph.D. Programs: Gender, Race, and Language . . . . . | 81  |
| 3.1   | Introduction . . . . .                                            | 81  |
| 3.2   | Peer Diversity in Higher Education . . . . .                      | 84  |
| 3.2.1 | Conceptual Framework . . . . .                                    | 88  |
| 3.3   | Data . . . . .                                                    | 89  |
| 3.3.1 | Outcome Measures . . . . .                                        | 90  |
| 3.3.2 | Measuring Cohort Composition . . . . .                            | 92  |
| 3.4   | Empirical Strategy . . . . .                                      | 97  |
| 3.4.1 | Baseline Specification . . . . .                                  | 97  |
| 3.4.2 | Identification Assumptions and Empirical Checks . . . . .         | 99  |
| 3.5   | Results . . . . .                                                 | 103 |

|       |                                                                                                           |     |
|-------|-----------------------------------------------------------------------------------------------------------|-----|
| 3.5.1 | On-Time Completion . . . . .                                                                              | 103 |
| 3.6   | Mechanism Analysis . . . . .                                                                              | 113 |
| 3.6.1 | Dropout by Year . . . . .                                                                                 | 113 |
| 3.6.2 | Grades . . . . .                                                                                          | 116 |
| 3.7   | Additional Analyses and Robustness Checks . . . . .                                                       | 119 |
| 3.7.1 | Alternative Peer-Composition Measures . . . . .                                                           | 119 |
| 3.7.2 | Heterogeneity by STEM Status . . . . .                                                                    | 120 |
| 3.7.3 | Race/ethnicity Diversity Among Domestic and International Students                                        | 124 |
| 3.7.4 | Country-of-Origin Diversity and Language Distance . . . . .                                               | 126 |
| 3.7.5 | Robustness to Minimum Cohort Size . . . . .                                                               | 127 |
| 3.8   | Discussion and Conclusion . . . . .                                                                       | 129 |
|       | Bibliography . . . . .                                                                                    | 131 |
| A     | Additional Tables and Figures . . . . .                                                                   | 140 |
| A.1   | Proportion of Students with Double Majors by Cohort . . . . .                                             | 140 |
| A.2   | Heterogeneity Within Broad Fields . . . . .                                                               | 140 |
| A.2.1 | Comparison with High- and Low-Return Benchmarks . . . . .                                                 | 140 |
| A.3   | Estimated Probability of Graduate Degree Attainment by Double-Major Com-<br>bination and Gender . . . . . | 140 |
| A.4   | Heterogeneity by Age . . . . .                                                                            | 140 |
| B     | Additional Tables and Figures for International Peer Effects . . . . .                                    | 149 |
| C     | Additional Tables and Figures for Diversity in Doctoral Programs . . . . .                                | 151 |
| C.1   | Country-Level Linguistic Distance from the United States . . . . .                                        | 151 |
| C.2   | Pairwise Linguistic Distance among Major Countries of Origin . . . . .                                    | 153 |
| C.3   | Country-of-Origin Mapping Used to Impute Missing Race/Ethnicity . . . . .                                 | 154 |

# List of Figures

|     |                                                                                                                                                                                                                                                                                            |     |
|-----|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----|
| 2.1 | Correlation between cohort international composition and program-demeaned covariates. Panels display cohort size, average age, and female share. Reported lines are fitted values from regressions of each covariate on international share. . . . .                                       | 55  |
| 2.2 | Distribution of Average Cohort Size Across Programs . . . . .                                                                                                                                                                                                                              | 63  |
| 2.3 | Dropout and graduation rates by year of enrollment. The x-axis measures program year. The y-axis indicates the fraction of students in the main estimation sample belonging to each category, dropped out, graduated, or still enrolled, measured at the end of each program year. . . . . | 75  |
| 3.1 | Race/Ethnicity Composition of Doctoral Students by International Status .                                                                                                                                                                                                                  | 94  |
| 3.2 | Race/Ethnicity Composition of Doctoral Students by International Status and Field . . . . .                                                                                                                                                                                                | 95  |
| 3.3 | Country-of-Origin Frequency and English-Language Distance . . . . .                                                                                                                                                                                                                        | 96  |
| 3.4 | Distribution of Program-Level Diversity Measures . . . . .                                                                                                                                                                                                                                 | 98  |
| 3.5 | Distribution of Program-Level Diversity Measures by STEM Status . . . . .                                                                                                                                                                                                                  | 112 |
| 3.6 | GPA Distributions by International Status . . . . .                                                                                                                                                                                                                                        | 117 |
| 3.7 | Relationship Between Country-of-Origin Diversity and Language Distance .                                                                                                                                                                                                                   | 126 |
| A.1 | Proportion of Students with Double Majors by Cohort . . . . .                                                                                                                                                                                                                              | 141 |
| A.2 | Income Dispersion Across Detailed Fields . . . . .                                                                                                                                                                                                                                         | 142 |
| B1  | Average Cohort Size and International Student Share by Ph.D. Entry Year .                                                                                                                                                                                                                  | 149 |

# List of Tables

|      |                                                                                                                             |    |
|------|-----------------------------------------------------------------------------------------------------------------------------|----|
| 1.1  | Summary Statistics . . . . .                                                                                                | 12 |
| 1.2  | Summary Statistics by Major Status and Highest Degree . . . . .                                                             | 13 |
| 1.3  | Distribution of Double Majors by Reported First and Second Field . . . . .                                                  | 13 |
| 1.4  | Double Majoring and Log Hourly Wages . . . . .                                                                              | 17 |
| 1.5  | Global and Local Effects of Double Majoring . . . . .                                                                       | 20 |
| 1.6  | Global and Local Effects of Double Majoring by Gender . . . . .                                                             | 23 |
| 1.7  | Hourly Wages by Major & Degree . . . . .                                                                                    | 26 |
| 1.8  | Double Majors and Post-Baccalaureate Highest Degree Attainment . . . . .                                                    | 27 |
| 1.9  | Double Majors and Likelihood of Working in a STEM Occupation . . . . .                                                      | 30 |
| 1.10 | Global and Local Effects of Double Majoring on First Major–Occupation<br>Match by Gender . . . . .                          | 33 |
| 1.11 | Alternative Major Ordering Rules . . . . .                                                                                  | 36 |
| 2.1  | Cohort-Level Characteristics by Field, 2005–2013 . . . . .                                                                  | 51 |
| 2.2  | Summary Statistics by International Status . . . . .                                                                        | 51 |
| 2.3  | Effect of Cohort International Composition on Ph.D. Completion . . . . .                                                    | 56 |
| 2.4  | Effect of Cohort International Composition on Ph.D. Completion within 7<br>Years: Heterogeneity by Field of Study . . . . . | 60 |
| 2.5  | Program-Level Characteristics by Program Size . . . . .                                                                     | 62 |
| 2.6  | Effect of Cohort International Composition on Ph.D. Completion within 7<br>Years: Heterogeneity by Program Size . . . . .   | 64 |
| 2.7  | Cohort-Level Characteristics by International-Share Threshold . . . . .                                                     | 67 |

|      |                                                                                                                              |     |
|------|------------------------------------------------------------------------------------------------------------------------------|-----|
| 2.8  | Effect of Cohort International Composition on Ph.D. Completion within 7 Years: Nonlinearity by International Share . . . . . | 68  |
| 2.9  | Effect of Cohort International Composition on GPA Outcomes: Heterogeneity by Field of Study . . . . .                        | 70  |
| 2.10 | Effect of Cohort International Composition on GPA Outcomes: Nonlinearity by International Share . . . . .                    | 72  |
| 2.11 | Effect of Cohort International Composition on Ph.D. Dropout by Field . . .                                                   | 76  |
| 2.12 | Effect of Cohort International Composition on Ph.D. Dropout: Nonlinearity by International Share . . . . .                   | 78  |
| 3.1  | Summary Statistics . . . . .                                                                                                 | 92  |
| 3.2  | Summary Statistics of Cohort Composition Measures . . . . .                                                                  | 97  |
| 3.3  | Balance Tests Across Cohort Characteristics . . . . .                                                                        | 101 |
| 3.4  | Residualized Correlations Among Cohort Diversity Measures . . . . .                                                          | 103 |
| 3.5  | Effects of Diversity Measures on 7-Year Ph.D. Completion . . . . .                                                           | 103 |
| 3.6  | Heterogeneous Effects of Cohort Composition on 7-Year Ph.D. Completion .                                                     | 107 |
| 3.7  | Nonlinear Effects Using Linear Spline Specification . . . . .                                                                | 110 |
| 3.8  | Summary Statistics by STEM Status . . . . .                                                                                  | 112 |
| 3.9  | Effects of Diversity Measures on 7-Year Ph.D. Completion by STEM Status                                                      | 113 |
| 3.10 | Heterogeneous Effects of Diversity Measures on Dropout by Year . . . . .                                                     | 115 |
| 3.11 | Heterogeneous Effects of Cohort Composition on Academic Performance . .                                                      | 118 |
| 3.12 | Alternative Peer-Composition Measures and 7-Year Ph.D. Completion . . . .                                                    | 121 |
| 3.13 | Heterogeneous Effects of Peer-Composition Measures on 7-Year Ph.D. Completion . . . . .                                      | 122 |
| 3.14 | Heterogeneous Effects by STEM Status . . . . .                                                                               | 123 |
| 3.15 | Summary Statistics of Race/Ethnicity Diversity Measures . . . . .                                                            | 124 |
| 3.16 | Pairwise Correlations Among Race/Ethnicity Diversity and Language Distance Measures . . . . .                                | 125 |

|      |                                                                                                  |     |
|------|--------------------------------------------------------------------------------------------------|-----|
| 3.17 | Effects of Race/Ethnicity Diversity Measures on 7-Year Ph.D. Completion . . . . .                | 125 |
| 3.18 | Country-of-Origin Diversity, Language Distance, and Completion . . . . .                         | 127 |
| 3.19 | Robustness of Diversity Effects by Minimum Cohort Size . . . . .                                 | 128 |
| A.1  | Classification of ACS Detailed Field-of-Degree Codes: Arts, Business, and<br>Education . . . . . | 143 |
| A.2  | ACS Field Codes: Engineering and Math/Science . . . . .                                          | 144 |
| A.3  | Double-Major Wages/Earnings Effects Relative to High- and Low-Income<br>Benchmarks . . . . .     | 145 |
| A.4  | Double Majors and Post-Baccalaureate Degree Attainment: Female Sample . . . . .                  | 146 |
| A.5  | Double Majors and Post-Baccalaureate Degree Attainment: Male Sample . . . . .                    | 147 |
| A.6  | Global and Local Effects of Double Majoring by Age . . . . .                                     | 148 |
| B1   | Summary Statistics by Field . . . . .                                                            | 150 |
| C1   | Country-Level Linguistic Distance from the United States . . . . .                               | 151 |
| C2   | Pairwise Linguistic Distance among Major Countries of Origin . . . . .                           | 153 |
| C3   | Country-of-Origin Mapping Used to Impute Missing Race/Ethnicity . . . . .                        | 154 |

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# Chapter 1

## The Double Major Dilemma

### 1.1 Introduction

A growing share of U.S. bachelor’s degree recipients report more than one undergraduate field of study.<sup>1</sup> Many students view double majoring as a way to improve labor-market prospects ([Pitt and Tepper, 2012](#)).<sup>2</sup> This belief is consistent with a simple intuition: if education raises earnings, then acquiring an additional field of training should increase the stock of human capital and expand post-college opportunities. Yet this intuition overlooks a central economic trade-off. Because students face limited time, attention, and curricular capacity, investment in a second field may come at the expense of deeper specialization in the first.<sup>3</sup>

This trade-off implies that the returns to a second major need not be uniform. A second major may raise earnings if it adds complementary human capital or improves access to occupations that reward a broader mix of skills. But it may also have limited or even

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<sup>1</sup>Studies using the National Survey of College Graduates (NSCG) typically place the share of double majors at around 16–20 percent, depending on the sample restrictions, while our American Community Survey (ACS) sample yields a somewhat lower estimate of about 11 percent (see [Figure A.1](#)).

<sup>2</sup>In Pitt and Tepper’s survey of double majors, 75.8 percent of respondents rated preparation for work as a very important or essential reason for double majoring.

<sup>3</sup>[Del Rossi and Hersch \(2008\)](#) note that double majoring does not appear to substantially increase time to bachelor’s degree completion.

negative returns if the additional coursework disperses students’ effort, reduces field-specific specialization, or weakens the link between academic training and subsequent occupations. We therefore ask whether the labor-market payoff to double majoring depends on field relatedness: do closely related majors generate higher returns than distant major combinations? The central hypothesis is that related majors are more likely to reinforce one another, whereas distant majors may involve a trade-off between breadth and specialization.

Following [Hanks et al. \(2024\)](#), we use the distinction between *local* and *global* double majors to capture the distance between fields. Local double majors combine fields within the same broad disciplinary area, whereas global double majors combine fields across broad disciplinary areas.<sup>4</sup> This distinction provides a tractable empirical proxy for the distance between fields and for the opportunity cost of academic diversification.

Using data from the 2010–2019 American Community Survey (ACS), we examine the wage returns to double majoring across combinations of fields. The ACS is well-suited for this study because it reports both a first and second field of bachelor’s degree for individuals with multiple majors, along with detailed labor-market outcomes and demographic characteristics.<sup>5</sup> We restrict the sample to full-time workers aged 30 to 60 with at least a bachelor’s degree, allowing us to study labor-market outcomes after individuals have likely completed schooling and entered stable employment.

Our empirical analysis compares students who double major with students who pursue a single major in the same reported first-field category and estimates separate wage differences for local and global second fields. This analysis yields three main findings. First, the average return to double majoring masks substantial heterogeneity across field combinations: local double majors are associated with positive wage premiums across most fields, whereas global double majors do not uniformly earn higher wages. In particular, individuals whose reported first major is in a science, technology, engineering, or math (STEM) field experience wage

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<sup>4</sup>For example, accounting and finance, or mechanical engineering and electrical engineering, are classified as local combinations, while mechanical engineering and English, or biology and business, are classified as global combinations.

<sup>5</sup>The NSCG, a commonly used dataset in the double-major literature, does not distinguish completed second majors from minors or other secondary fields; we discuss this measurement issue in Section 1.4.

penalties when their second major lies outside the same broad area. Second, we show that the wage penalties and premiums associated with double majoring differ by gender in both magnitude and direction. The negative wage associations for global STEM double majors are concentrated among women: women with global STEM combinations earn significantly less than comparable single majors in the same reported first field, whereas men with similar combinations experience little or no penalty. By contrast, local double majors often show more favorable wage associations for women than for men, with women experiencing larger premiums in several local-field combinations. Third, occupational sorting appears to be an important mechanism for these gendered wage patterns. Individuals with global STEM combinations, especially women, are less likely to work in STEM-related occupations despite holding STEM degrees. We also find some evidence that first-major occupation match matters: local double majors are often more likely to work in occupations related to their reported first field, while global combinations are more likely to weaken this connection in some fields. These patterns help explain why global STEM double majors may experience lower earnings, while some local combinations are associated with higher wages.

A distinctive feature of our analysis is that we explicitly account for reported major order when modeling the wage associations of double majoring. Existing studies typically either treat the two fields as an unordered degree bundle (e.g., [Del Rossi and Hersch, 2008, 2016](#)) or benchmark double-major graduates against single-major graduates from the higher- and lower-paying fields in the degree pair (e.g., [Uddin and Tout, 2020](#); [Zhu and Zhang, 2021](#)). Because our empirical framework uses the first reported field as the reference field, understanding whether reported order carries economic meaning is important for constructing an appropriate model of how double majoring is associated with wages. While the ACS reports fields of degree in first and second order, it does not reveal the criteria respondents use to determine that order. Therefore, to assess whether reported order carries meaningful information, we examine how wage outcomes change when field order is switched, randomized, reordered so that the higher-paying field is listed first, or reordered alphabetically. If wage outcomes remain invariant under these alternative orderings, reported order would have little

substantive relevance. By contrast, differences across these orderings would suggest that the reported first field is not simply interchangeable with the second field; rather, reported order may carry economic meaning by reflecting differences in the relative role or salience of each major in shaping subsequent labor-market outcomes. In particular, if respondents list first the field they view as their primary area of specialization, the field most closely tied to their intended occupation, or the credential most central to their labor-market identity, then our approach of using the first reported major as the reference field is appropriate.

The findings in this paper have implications for how students, universities, and policy-makers think about double majoring. Double majoring is often presented as an unambiguous enhancement to a student’s educational portfolio. Our results show, however, that double majoring is not always associated with positive labor-market outcomes. A second major can raise earnings when it complements the primary field or provides human capital not supplied by the first field and helps students move into higher-paying occupations. For students whose reported first field is in Humanities and Social Sciences, even global combinations are associated with higher wages, suggesting that adding a distant field can expand access to occupations that the first field alone may not reach. By contrast, global combinations may carry costs when the reported first field is tied to specialized, high-return occupational pathways, especially for women in STEM. The economic value of double majoring therefore depends not simply on acquiring more credentials, but on how the two fields work together and shape the occupations graduates enter.

The remainder of this chapter is organized as follows. Section 1.2 reviews the related literature. Section 1.3 develops the conceptual framework. Section 1.4 describes the ACS sample and the construction of local and global double-major measures. Section 1.5 presents the empirical strategy. Section 1.6 reports the main wage estimates and gender heterogeneity. Section 1.7 examines potential mechanisms, including graduate education, STEM occupation sorting, and occupation-field match. Section 1.8 discusses the role of reported major ordering, and Section 1.9 concludes.

## 1.2 Related Literature

This paper contributes to three related literatures. First, it adds to the literature on the labor-market returns to college majors, which shows that fields of study differ substantially in earnings and occupational pathways (Altonji et al., 2012; Kirkeboen et al., 2016). We extend this literature by showing that the value of a field depends not only on the primary major itself, but also on how it is combined with another field. Second, the paper contributes to research on the labor-market value of double majoring, which has generally documented positive average returns but has paid less attention to heterogeneity across field combinations (e.g., Del Rossi and Hersch, 2008; Hanks et al., 2024). We show that double majoring is not a single treatment: its returns vary systematically with the distance between fields, and for some field combinations, they may even turn negative on labor market returns. Third, the paper contributes to research on occupational match and gender differences in STEM pathways (Robst, 2007; Sloane et al., 2021). We document that women with global STEM combinations are especially likely to sort away from STEM occupations, helping explain why some double-major combinations are associated with lower earnings.

### 1.2.1 College Majors and Field-Specific Human Capital

A large literature shows that college majors are strongly associated with labor-market outcomes (Grogger and Eide, 1995; Altonji et al., 2012; Kirkeboen et al., 2016; Altonji et al., 2016). College majors differ not only in average earnings but also in the types of occupations to which they lead, suggesting that fields of study represent distinct forms of human capital rather than interchangeable units of schooling. Arcidiacono (2004) shows that returns to college major vary substantially across fields and that these differences are closely related to ability sorting and major choice. Altonji et al. (2012) provide a broader framework in which curriculum, college major, and career choices are understood as heterogeneous human-capital investments. More recently, Kirkeboen et al. (2016) use variation in admission cutoffs and students' ranked preferences to show that field of study has sizable effects on earnings.

This literature motivates our focus on combinations of majors. If fields generate different types of human capital and lead to different occupational pathways, then the value of a second major should depend on how it interacts with the first. A second major in a related field may deepen or complement the primary field of training, whereas a second major in a distant field may broaden skills while reducing specialization. Our analysis extends the college-major literature by studying not only the return to a single field, but also the return to bundles of fields.

## 1.2.2 The Returns to Double Majoring

A related literature examines whether double majoring improves labor-market outcomes. Early studies generally find positive earnings differences associated with completing more than one major. Using the National Survey of College Graduates, [Del Rossi and Hersch \(2008\)](#) find that double majors earn more than comparable single majors, although returns vary substantially across field combinations. [Hemelt \(2010\)](#) similarly documents positive earnings differences associated with double majoring. More recent work, however, points to a more nuanced interpretation. [Del Rossi and Hersch \(2016\)](#) examine both private and social benefits, including earnings, R&D activity, job match, and job satisfaction. They find no evidence of a general earnings premium; instead, the returns are concentrated in particular combinations, especially business–STEM pairings.

Recent work has therefore begun to move beyond average effects by examining how returns vary with the composition of the degree bundle. The closest paper to ours is [Uddin and Tout \(2020\)](#), who also use the American Community Survey and show that dual majors earn more than graduates from the lower-paying single major, but do not outperform graduates from the higher-paying single major. Using the Baccalaureate and Beyond Longitudinal Study data, [Zhu and Zhang \(2021\)](#) similarly show that double-major graduates face an initial earnings penalty relative to graduates from the higher-paying field, but earn more than graduates from the lower-paying field. These results parallel our findings. Since STEM fields generally have higher expected post-graduation earnings, STEM students who

double major are structurally more likely to pair their STEM major with a lower-paying field. This composition effect helps explain why graduates whose first major is in STEM may earn less on average than single STEM majors, not because double majoring is uniformly disadvantageous, but because its returns depend on the earnings profile of the paired field.

[Hanks et al. \(2024\)](#) move beyond earnings levels and show that double majoring can reduce exposure to labor market shocks. In particular, they find that global double majors, whose fields span broader academic categories, are more protected against shocks than local double majors. This suggests that, although some double-major combinations may lower average earnings in our setting, double majoring is not necessarily a bad choice; broader combinations may provide insurance by expanding graduates' skill portfolios and labor market options.

Our paper contributes by distinguishing the earnings rank of the second major from the relatedness of the two majors. Higher earnings may simply reflect adding a higher-paying field, while lower earnings may reflect adding a lower-paying field. We therefore separate this earnings-rank channel from the local–global distinction at the center of our analysis. Local double majors combine fields within the same broad area and may reinforce field-specific skills, while global double majors combine more distant fields and may broaden training at the cost of specialization. This distinction allows us to ask whether the returns to double majoring reflect the earnings profile of the second field or the way the two fields complement, redirect, or dilute each other.

### 1.2.3 Occupational Match and Gender

The return to a college major depends in part on whether graduates use their field-specific skills in the occupations they enter. Workers employed in jobs less related to their field of study earn lower wages ([Robst, 2007](#)), and this mismatch penalty has increased over time among college-educated workers ([Cassidy and Gaulke, 2024](#)). These findings motivate a

central mechanism in our analysis: double majors may affect earnings not only by adding skills or credentials, but also by changing the occupations into which graduates sort.

This occupational-sorting channel is especially important for understanding gender differences. A large literature shows that part of the gender wage gap among college graduates arises before labor-market entry, through gendered choices of field of study: women are less likely to select majors associated with high potential wages and, conditional on major, tend to enter occupations with lower potential earnings ([Brown and Corcoran, 1997](#); [Black et al., 2008](#); [Sloane et al., 2021](#)). Yet this literature largely treats field of study as a single or primary major, leaving double-major combinations outside the main account of how specialization maps into occupations and earnings. We study double majors as an additional margin of specialization and ask whether men and women with the same first major experience different labor-market outcomes depending on the second major they choose.

### 1.3 Conceptual Framework

We view double majoring as an investment in human capital under time and curricular constraints. A second major can increase earnings if it adds useful skills, strengthens the student’s reported first field, improves occupational match, or opens access to higher-paying occupations. But the return need not always be positive. Because students have limited time and course capacity, completing a second major may also reduce investment in the first field, weaken specialization, or redirect graduates toward occupations less closely tied to their primary field of training. The labor-market return to double majoring is therefore theoretically ambiguous.

Field relatedness is central to this ambiguity. Prior work has shown that double majoring does not substantially increase time to bachelor’s degree completion ([Del Rossi and Hersch, 2008](#)). If double majors complete college in roughly the same amount of time as single majors, then the second major is likely obtained by reallocating coursework, effort, and attention within a relatively fixed undergraduate program. This reallocation should be less costly when

the two fields are closely related. For example, electrical engineering and computer science may share prerequisites, quantitative methods, and technical coursework. In such cases, the second major can reinforce the first by adding related skills at relatively low marginal cost.

The trade-off may be larger when the two fields are distant. A student combining electrical engineering with music history, for example, may face fewer overlapping requirements and less shared skill content. Completing the second major may then crowd out advanced electives or other forms of specialized investment in the first field. In this case, the second major broadens the student’s educational portfolio but may weaken field-specific specialization.

Ideally, one would measure the distance between every pair of majors continuously and estimate how returns vary along that margin. Because the ACS does not provide detailed information on course-taking, degree requirements, or the overlap between fields, we use the distinction between local and global double majors as an empirical proxy for field relatedness. This framework motivates our empirical analysis of whether the returns to double majoring differ systematically between local and global combinations, and whether those differences reflect complementarities between fields or the earnings profile of the added major.

## 1.4 Data

We use the American Community Survey (ACS), pooled over survey years 2010–2019.<sup>6</sup> The ACS is a large, nationally representative repeated cross-section of the U.S. population that reports earnings, labor supply, education, demographic characteristics, geographic location, and fields of bachelor’s degree.

The ACS is particularly well suited for this study because it identifies completed bachelor’s fields separately from less intensive secondary degrees, such as minors and certificates. We classify individuals as double majors when they report two bachelor’s fields. Most sur-

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<sup>6</sup>We use the 2010–2019 period because ACS information on second fields of degree is not available before 2009, the STEM occupation classification used in the mechanism analysis is available consistently beginning in 2010, and survey years 2020 and later may reflect labor-market disruptions associated with the COVID-19 pandemic.

veys used in the literature do not make this critical distinction. For example, the National Survey of College Graduates (NSCG) records a second field that includes both completed second majors and minors.<sup>7</sup> Consistent with this measurement difference, approximately 21 percent of college graduates report a second field in the NSCG, compared with estimates closer to 11 percent in the ACS and Baccalaureate and Beyond.<sup>8</sup> Because minors generally require fewer credits and less field-specific investment than completed second majors, combining minors with double majors may attenuate estimates of both the opportunity costs and labor-market returns associated with completing a second major.

We begin with individuals who report at least a bachelor’s degree and restrict the sample to full-time employed workers aged 30 to 60.<sup>9</sup> Full-time employment is defined as working at least 40 weeks in the previous year and at least 35 usual hours per week. This restriction focuses the analysis on workers with relatively stable labor-force attachment and on ages at which most individuals have completed schooling and entered the labor market. We exclude individuals with annual earnings below \$10,000 or above \$300,000,<sup>10</sup> with earnings deflated to 2010 dollars. The final pooled sample contains 2,283,895 individuals, of whom approximately 11 percent report two bachelor’s fields.

The main outcome is log hourly wage. Hourly wages are constructed by dividing annual earnings by the product of weeks worked in the previous year and usual hours worked per week. We also examine two mechanism outcomes. The first is graduate degree attainment, which captures whether double majors are more likely to acquire additional formal education after college. The second is employment in a STEM occupation, defined using Bureau of Labor Statistics occupation codes, which allows us to examine whether double-major combinations are associated with sorting into occupations closely related to STEM fields of study.

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<sup>7</sup>Prior studies of double majoring have used several datasets. [Del Rossi and Hersch \(2008\)](#) and [Hemelt \(2010\)](#) use the 2003 National Survey of College Graduates (NSCG), while [Del Rossi and Hersch \(2016\)](#) use the 2010 NSCG. By contrast, [Jiang \(2019\)](#) uses the National Longitudinal Survey of Youth 1997 (NLSY97).

<sup>8</sup>Baccalaureate and Beyond distinguishes second majors from minors and concentrations.

<sup>9</sup>Among individuals aged 30–60 with a bachelor’s degree, 64.8 percent worked full-time, 14.8 percent worked part-time, and 20.4 percent did not work in the previous year.

<sup>10</sup>In the full sample, 4.01% of observations fall below the \$10,000 income cutoff and 3.74% exceed the \$300,000 cutoff.

The ACS reports detailed field-of-degree codes.<sup>11</sup> We aggregate these fields into five broad categories: Humanities and Social Sciences, Business and Economics, Education, Engineering, and Math and Natural Sciences.<sup>12</sup> Because the ACS documentation does not assign an economic interpretation to the ordering of first and second fields, we refer to the two fields as the “reported first field” and “reported second field.” In correspondence with the ACS, we were informed that the ordering reflects the sequence in which respondents list their degrees or fields in the survey. Section 1.8 examines the empirical importance of this ordering.

We classify double majors as local or global according to whether the reported first and second fields fall within the same broad category. A local double major combines two fields within the same broad category, such as accounting and finance. A global double major combines fields across broad categories, such as engineering and English. This distinction captures whether the second field represents additional specialization within a related area or a broader investment across more distant domains. In the ACS sample, approximately 57 percent of double majors are local combinations and 43 percent are global combinations.

Table 1.1 reports summary statistics for the estimation sample. Average annual income is approximately \$75,000, the average hourly wage is \$32.88, and 11 percent of individuals report two bachelor’s fields. Table 1.2 compares individuals who report one bachelor’s field with those who report two bachelor’s fields, separately by highest degree attained. Reporting two bachelor’s fields is more common among workers with a graduate degree: 12.51 percent of graduate-degree holders report two bachelor’s fields, compared with 10.04 percent among workers whose highest degree is a bachelor’s degree. Individuals who report two bachelor’s fields are also about 10 percentage points more likely than those who report one bachelor’s field to have a first field in humanities and social sciences, while they are about 5 percentage points less likely to have a first field in engineering.

Table 1.3 describes the distribution of double-major combinations by reported first and second field. Double majors are strongly local: for every first-field category, the largest

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<sup>11</sup>These are Census/ACS field-of-degree codes used to classify respondents’ undergraduate fields of study. See [IPUMS USA DEGFIELD codes](#).

<sup>12</sup>The detailed mapping from Census/ACS field-of-degree codes to these five categories is reported in Appendix Tables [A.1](#) and [A.2](#).

Table 1.1: Summary Statistics

| ACS 2010–2019 (N = 2,283,895)  |        |           |        |         |
|--------------------------------|--------|-----------|--------|---------|
| Variable                       | Mean   | Std. Dev. | Min    | Max     |
| <b>Economic Outcomes</b>       |        |           |        |         |
| Annual Income                  | 74,968 | 44,187    | 10,000 | 300,000 |
| Hourly Wage                    | 32.88  | 18.52     | 1.98   | 179.44  |
| Hours Worked per Week          | 45.20  | 7.95      | 36     | 99      |
| Weeks Worked per Year          | 50.62  | 1.59      | 43.5   | 51      |
| <b>Degree Structure</b>        |        |           |        |         |
| Double Major                   | 0.11   | 0.31      | 0      | 1       |
| Local Double Major             | 0.06   | 0.25      | 0      | 1       |
| <b>First Field of Study</b>    |        |           |        |         |
| Humanities and Social Sciences | 0.32   | 0.47      | 0      | 1       |
| Business and Economics         | 0.25   | 0.44      | 0      | 1       |
| Education                      | 0.12   | 0.32      | 0      | 1       |
| Engineering                    | 0.13   | 0.33      | 0      | 1       |
| Math and Natural Sciences      | 0.17   | 0.38      | 0      | 1       |
| <b>Demographic Variables</b>   |        |           |        |         |
| Age                            | 44.43  | 8.93      | 30     | 60      |
| Female                         | 0.49   | 0.50      | 0      | 1       |
| Married                        | 0.83   | 0.37      | 0      | 1       |
| Metropolitan                   | 0.82   | 0.39      | 0      | 1       |
| White                          | 0.88   | 0.33      | 0      | 1       |
| Black                          | 0.07   | 0.25      | 0      | 1       |
| Hispanic                       | 0.04   | 0.20      | 0      | 1       |
| Asian                          | 0.02   | 0.14      | 0      | 1       |
| Other Race                     | 0.03   | 0.16      | 0      | 1       |

*Notes:* Hourly wage is calculated as annual income divided by annual hours worked, where annual hours worked equals hours worked per week multiplied by weeks worked per year. Married is an indicator equal to one if the individual has been married at least once. Metropolitan is an indicator equal to one for individuals living in a metropolitan area.

share of second fields lies on the diagonal. These within-category combinations account for roughly one-half or more of second fields in all categories except Engineering. Humanities and Social Sciences is the most common reported second field overall, accounting for 40.69 percent of second fields. Engineering is the most outward-oriented category: only 40.89 percent of Engineering first-field students report an Engineering second field, while sizable shares combine Engineering with Business and Economics or Math and Natural Sciences. The off-diagonal patterns also indicate that cross-field combinations are not random: STEM fields are more tightly connected to other STEM fields, while non-STEM fields show stronger links to other non-STEM fields.

Table 1.2: Summary Statistics by Major Status and Highest Degree

| ACS 2010–2019 (N = 2,283,895)  |                                 |                               |                               |                               |
|--------------------------------|---------------------------------|-------------------------------|-------------------------------|-------------------------------|
| Variable                       | Bachelor’s Degree               |                               | Graduate Degree               |                               |
|                                | Single Major<br>(N = 1,257,644) | Double Major<br>(N = 140,377) | Single Major<br>(N = 775,023) | Double Major<br>(N = 110,851) |
|                                | Mean                            | Mean                          | Mean                          | Mean                          |
| <b>Economic Outcomes</b>       |                                 |                               |                               |                               |
| Annual Income                  | 70,098                          | 70,535                        | 82,485                        | 83,270                        |
| Hourly Wage                    | 30.99                           | 30.94                         | 35.89                         | 35.78                         |
| Hours Worked per Week          | 44.74                           | 45.06                         | 45.79                         | 46.43                         |
| Weeks Worked per Year          | 50.68                           | 50.67                         | 50.52                         | 50.51                         |
| <b>First Field of Study</b>    |                                 |                               |                               |                               |
| Humanities and Social Sciences | 0.30                            | 0.39                          | 0.34                          | 0.45                          |
| Business and Economics         | 0.31                            | 0.30                          | 0.17                          | 0.17                          |
| Education                      | 0.09                            | 0.06                          | 0.17                          | 0.10                          |
| Engineering                    | 0.15                            | 0.10                          | 0.11                          | 0.06                          |
| Math and Natural Sciences      | 0.15                            | 0.16                          | 0.21                          | 0.21                          |
| <b>Demographic Variables</b>   |                                 |                               |                               |                               |
| Age                            | 44.36                           | 43.61                         | 44.77                         | 43.94                         |
| Female                         | 0.46                            | 0.49                          | 0.52                          | 0.53                          |
| Married                        | 0.83                            | 0.79                          | 0.85                          | 0.81                          |
| Metropolitan                   | 0.81                            | 0.82                          | 0.83                          | 0.84                          |
| White                          | 0.88                            | 0.90                          | 0.87                          | 0.89                          |
| Black                          | 0.07                            | 0.05                          | 0.07                          | 0.05                          |
| Hispanic                       | 0.04                            | 0.04                          | 0.04                          | 0.03                          |
| Asian                          | 0.02                            | 0.02                          | 0.02                          | 0.03                          |
| Other Race                     | 0.03                            | 0.03                          | 0.02                          | 0.03                          |
| Distribution                   | 89.96%                          | 10.04%                        | 87.49%                        | 12.51%                        |

Table 1.3: Distribution of Double Majors by Reported First and Second Field

| Reported First Field   | Reported Second Field |                  |               |               |                  |
|------------------------|-----------------------|------------------|---------------|---------------|------------------|
|                        | Hum. & Soc. Sci.      | Business & Econ. | Education     | Engineering   | Math & Nat. Sci. |
| Humanities & Soc. Sci. | <b>65.60%</b>         | 12.78%           | 7.64%         | 3.90%         | 10.09%           |
| Business & Economics   | 22.18%                | <b>60.58%</b>    | 3.15%         | 8.10%         | 5.99%            |
| Education              | 27.24%                | 4.66%            | <b>56.05%</b> | 2.36%         | 9.68%            |
| Engineering            | 17.75%                | 19.71%           | 2.10%         | <b>40.89%</b> | 19.55%           |
| Math & Nat. Sci.       | 24.29%                | 9.77%            | 5.45%         | 10.06%        | <b>50.43%</b>    |
| <b>Total</b>           | 40.69%                | 23.64%           | 9.45%         | 8.94%         | 17.28%           |

*Note.* Entries are row percentages. Each body row shows how double majors with a given reported first field are distributed across reported second fields. Bold diagonal entries indicate cases where the reported first and second fields fall in the same broad field category. The total row shows the overall distribution of reported second fields.

## 1.5 Empirical Strategy

We estimate the association between double majoring and labor-market outcomes using log-wage regressions that compare double and single majors within the same reported first-field category. For example, among individuals whose first reported major is Economics, we compare wages between those with and without a second major. The resulting estimate captures wage differences associated with double majoring within first-field categories. The baseline specification is

$$\begin{aligned} \log(wage_{icst}) = & \sum_{m=2}^5 \beta_{1m} F_{im} + \beta_2 DM_i + \sum_{m=2}^5 \beta_{3m} (F_{im} \times DM_i) \\ & + X_i' \Gamma + \rho U_{st} + \gamma_c + \theta_s + \varepsilon_{icst}. \end{aligned} \quad (1.1)$$

where subscripts  $i$ ,  $c$ ,  $s$ , and  $t$  refer to individuals, graduation cohorts, current states of residence, and survey years, respectively. The outcome  $\log(wage_{icst})$  is the log hourly wage.  $F_{im}$  is an indicator equal to one if individual  $i$ 's reported first field belongs to category  $m$ .<sup>13</sup> Humanities and Social Sciences is the omitted reference category.  $DM_i$  is an indicator equal to one if individual  $i$  reports two fields of bachelor's degree.  $X_i$  includes individual demographic and labor-market controls: age, age-squared, gender, race, marital status, and metropolitan status. Marital status is coded as one if the individual has been married at least once and zero otherwise.<sup>14</sup> Metropolitan status is coded as zero if the individual is not associated with a metropolitan area, and one if the individual lives in a metropolitan area, in a surrounding metropolitan area, or in a mixed metropolitan classification. To account for contemporaneous economic conditions in the individual's current state of residence, I also control for the annual state-level unemployment rate,  $U_{st}$ , obtained from the U.S. Bureau of Labor Statistics. The model includes graduation cohort fixed effects,  $\gamma_c$ , and state fixed effects,  $\theta_s$ .<sup>15</sup> Standard errors are clustered by graduation cohort and current state of residence.

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<sup>13</sup>The five field categories are Humanities and Social Sciences, Business and Economics, Education, Engineering, and Math and Natural Sciences.

<sup>14</sup>The data do not allow me to distinguish currently married individuals from those who were previously married but are now divorced, separated, or widowed.

<sup>15</sup>Survey-year fixed effects are omitted because graduation cohort is constructed as  $c = \text{year} - \text{age} + 22$ .

Clustering by graduation cohort and current state accounts for correlated shocks among individuals who entered the labor market under similar conditions or share local labor-market and state-specific factors.

In this specification,  $\beta_2$  measures the wage difference associated with double majoring among individuals whose reported first field is in Humanities and Social Sciences. For individuals whose reported first field is  $m \in [2, 5]$ , the corresponding double-major wage difference is  $\beta_2 + \beta_{3m}$ . These estimates allow the association between double majoring and wages to vary by reported first field.

To examine whether returns differ between local and global double majors, we estimate an extended specification:

$$\begin{aligned} \log(wage_{icst}) = & \sum_{m=2}^5 \beta_{1m} F_{im} + \beta_2 DM_i + \sum_{m=2}^5 \beta_{3m} (F_{im} \times DM_i) \\ & + \beta_4 (DM_i \times Local_i) + \sum_{m=2}^5 \beta_{5m} (F_{im} \times DM_i \times Local_i) \\ & + X_i' \Gamma + \rho U_{st} + \gamma_c + \theta_s + \varepsilon_{icst}. \end{aligned} \quad (1.2)$$

Here,  $Local_i$  is an indicator equal to one if the first and second fields belong to the same broad category. Since  $Local_i$  is only defined for individuals with two fields, it enters the model through interactions with  $DM_i$ . In this specification,  $\beta_2 + \beta_{3m}$  gives the wage difference associated with a global double major for individuals whose reported first field is  $m$ , relative to single majors in the same first-field category. The corresponding wage difference for local double majors is  $\beta_2 + \beta_{3m} + \beta_4 + \beta_{5m}$ .

Finally, these estimates should be interpreted as conditional associations rather than causal effects. Although the specifications compare double majors to single majors within the same reported first-field category and control for observable demographic characteristics, cohort differences, state fixed effects, and contemporaneous state labor-market conditions, double majoring is not randomly assigned. Students who complete two majors may differ from single majors in unobserved ability, motivation, family background, or career prefer-

ences. If students with stronger academic preparation or higher labor-market potential are more likely to double major, the estimated wage differences would be biased upward relative to the causal effect of double majoring. Bias in the opposite direction is also possible if double majoring is chosen by students with weaker initial labor-market prospects.

We take this selection concern seriously and conduct two exploratory analyses using datasets that contain information unavailable in the ACS. First, using the NLSY97, we find that individuals with higher ASVAB scores are more likely to double major, suggesting that double majors may be positively selected on pre-college academic preparation.<sup>16</sup> Second, using the NSCG, we find no statistically significant relationship between mother’s education and the probability of reporting more than one undergraduate field. This suggests that observable family-background differences, at least as proxied by mother’s education, are unlikely to explain the main ACS patterns. These checks do not eliminate selection concerns. They do, however, suggest two points: academic preparation appears to matter for double-major choice, while this relationship is not mirrored by a simple measure of family background.

Recovering a causal estimate is outside the scope of this paper because the ACS does not contain the institutional rules, transcript histories, pre-college preparation measures, or timing of major choices needed to isolate exogenous variation in double-major completion. A causal design would require variation that changes the cost or feasibility of double majoring while being otherwise unrelated to potential wages, such as institution-by-cohort changes in degree requirements, credit limits, advising rules, or other policy shifts affecting access to double majors. In the absence of such variation, the estimates are best read as descriptive evidence on how wage outcomes differ across single majors, global double majors, and local double majors after conditioning on observed characteristics.

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<sup>16</sup>ASVAB stands for the Armed Services Vocational Aptitude Battery, a standardized aptitude test commonly used in labor and education research as a proxy for cognitive skills or pre-college academic preparation. In the NLSY97, a one-point increase in the ASVAB percentile rank is associated with a 0.18 percentage point increase in the probability of double majoring. A ten-percentile-point increase therefore corresponds to a 1.8-percentage-point increase in the probability of double majoring.

Table 1.4: Double Majoring and Log Hourly Wages

| Parameter                                                                                 | First Field                  | Highest Degree Type  |                      |                      |
|-------------------------------------------------------------------------------------------|------------------------------|----------------------|----------------------|----------------------|
|                                                                                           |                              | All<br>(1)           | Bachelor's<br>(2)    | Graduate<br>(3)      |
| <i>Panel A. First-field wage differences relative to Humanities &amp; Social Sciences</i> |                              |                      |                      |                      |
| $\beta_{12}$                                                                              | Business & Economics         | 0.157***<br>(0.002)  | 0.154***<br>(0.002)  | 0.163***<br>(0.003)  |
| $\beta_{13}$                                                                              | Education                    | -0.106***<br>(0.002) | -0.127***<br>(0.003) | -0.088***<br>(0.003) |
| $\beta_{14}$                                                                              | Engineering                  | 0.280***<br>(0.003)  | 0.286***<br>(0.003)  | 0.263***<br>(0.003)  |
| $\beta_{15}$                                                                              | Math & Natural Sciences      | 0.166***<br>(0.002)  | 0.149***<br>(0.003)  | 0.190***<br>(0.003)  |
| <i>Panel B. Double-major wage differences within first field</i>                          |                              |                      |                      |                      |
| $\beta_2$                                                                                 | Humanities & Social Sciences | 0.020***<br>(0.002)  | 0.022***<br>(0.003)  | 0.020***<br>(0.003)  |
| $\beta_2 + \beta_{32}$                                                                    | Business & Economics         | 0.034***<br>(0.003)  | 0.038***<br>(0.003)  | 0.026***<br>(0.005)  |
| $\beta_2 + \beta_{33}$                                                                    | Education                    | 0.026***<br>(0.004)  | 0.031***<br>(0.007)  | 0.018***<br>(0.005)  |
| $\beta_2 + \beta_{34}$                                                                    | Engineering                  | -0.009*<br>(0.005)   | -0.003<br>(0.006)    | -0.014*<br>(0.008)   |
| $\beta_2 + \beta_{35}$                                                                    | Math & Natural Sciences      | -0.017***<br>(0.003) | -0.007<br>(0.004)    | -0.031***<br>(0.005) |
| Observations                                                                              |                              | 2,278,694            | 1,394,548            | 884,146              |

*Notes:* The dependent variable is log hourly wage. Panel A reports first-field wage differences relative to Humanities & Social Sciences. Panel B reports the estimated wage difference associated with double majoring within each reported first-field category. All specifications include individual controls, the state unemployment rate, graduation cohort fixed effects, and state fixed effects. Standard errors are clustered by graduation cohort and current state. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

## 1.6 Results

### 1.6.1 Average Returns to Double Majoring

Table 1.4 reports estimates from the baseline wage specification. Column (1) uses the full ACS sample, column (2) restricts the sample to individuals whose highest degree is a bachelor's degree, and column (3) restricts the sample to individuals with a graduate degree. Panel A confirms wage differences across reported first fields. Relative to Humanities and Social Sciences, Business and Economics, Engineering, and Math and Natural Sciences are

associated with substantially higher wages, while Education is associated with lower wages. These differences are consistent with the broader evidence that college majors differ markedly in labor-market returns ([Arcidiacono, 2004](#); [Altonji et al., 2012](#); [Kirkeboen et al., 2016](#)).

Panel B shows that the wage differences associated with completing a second major vary sharply by first field. In the full sample, individuals whose first field is Humanities and Social Sciences, Business and Economics, or Education earn 2.0–3.4 percent more when they complete a second major than comparable individuals with a single major in the same first field. In contrast, the estimate is small, negative, and only marginally significant for Engineering, while it is larger in magnitude and statistically significant for Math and Natural Sciences.

The same non-STEM/STEM contrast appears in both the bachelor’s-only and graduate-degree samples. The estimated double-major wage premium is positive and statistically significant for non-STEM first fields, while the estimates for STEM first fields are close to zero in the bachelor’s-only sample and negative in the graduate-degree sample. These results differ from prior evidence on workers with graduate degrees. In particular, [Del Rossi and Hersch \(2008\)](#) find no statistically significant wage effect of double majoring among workers with graduate degrees. In our ACS sample, however, the estimated double-major premium remains statistically significant for some graduate-degree holders, and its direction varies systematically by undergraduate first field.

The comparison with prior work highlights two additional points. First, our results are consistent with prior literature showing that the average wages premium associated with double majoring is positive but modest. Using the 2003 NSCG, [Del Rossi and Hersch \(2008\)](#) estimate a 2.3 percent wage premium among bachelor’s-only workers, and [Hemelt \(2010\)](#) estimates an average premium of about 3.2 percent. Using ACS data, [Uddin and Tout \(2020\)](#) similarly reports only a small premium when double majors are compared with single majors in their reported first major. Averaged across fields, our results point in the same direction. However, we show that the positive double-major premium is far from uniform across first fields. It is concentrated among Humanities and Social Sciences, Business and

Economics, and Education, and is negative for workers whose first field is Math and Natural Sciences.

Second, although prior work has not stated the null or negative estimates for STEM first fields as directly, several earlier findings point in this direction. [Uddin and Tout \(2020\)](#) and [Zhu and Zhang \(2021\)](#) show that double majors earn more than single majors in the lower-paying field in the pair, but less than single majors in the higher-paying field. Because STEM fields generally have higher average earnings than non-STEM fields, this pattern suggests that adding a lower-return field to a high-return STEM field may yield little additional wage gain.

This interpretation, however, should be treated with caution. STEM is not synonymous with high returns, and non-STEM is not synonymous with low returns.<sup>17</sup> Some STEM fields have lower average returns than some non-STEM fields. For example, even among workers whose first field is Engineering, some may come from relatively low-earning engineering subfields and add a higher-return non-STEM field, such as Economics. In such cases, STEM-first double majors cannot be interpreted simply as workers adding a lower-return second field. Similarly, as shown in [Table 1.3](#), many double majors are local combinations within the same broad field category, and a large share of STEM-first double majors add another STEM field. Thus, the zero or negative estimates for STEM-first fields may partly reflect the particular second fields these workers choose, but this channel is unlikely to fully account for the pattern.<sup>18</sup> These estimates may also reflect diminishing marginal returns when the first field already provides strong occupation-specific skills, or a tradeoff between breadth and depth in highly technical fields. We examine these possibilities below by separating local and global double majors.

Table 1.5: Global and Local Effects of Double Majoring

| Parameter                                                               | First Field                  | Highest Degree Type  |                      |                      |
|-------------------------------------------------------------------------|------------------------------|----------------------|----------------------|----------------------|
|                                                                         |                              | All<br>(1)           | Bachelor's<br>(2)    | Graduate<br>(3)      |
| <i>Panel A. Global double-major wage differences within first field</i> |                              |                      |                      |                      |
| $\beta_2$                                                               | Humanities & Social Sciences | 0.045***<br>(0.003)  | 0.051***<br>(0.004)  | 0.038***<br>(0.005)  |
| $\beta_2 + \beta_{32}$                                                  | Business & Economics         | -0.007<br>(0.005)    | -0.005<br>(0.006)    | -0.009<br>(0.007)    |
| $\beta_2 + \beta_{33}$                                                  | Education                    | 0.035***<br>(0.006)  | 0.055***<br>(0.009)  | 0.017**<br>(0.008)   |
| $\beta_2 + \beta_{34}$                                                  | Engineering                  | -0.038***<br>(0.006) | -0.025***<br>(0.007) | -0.058***<br>(0.011) |
| $\beta_2 + \beta_{35}$                                                  | Math & Natural Sciences      | -0.030***<br>(0.005) | -0.009<br>(0.006)    | -0.055***<br>(0.006) |
| <i>Panel B. Local double-major wage differences within first field</i>  |                              |                      |                      |                      |
| $\beta_2 + \beta_4$                                                     | Humanities & Social Sciences | 0.007***<br>(0.003)  | 0.005<br>(0.004)     | 0.012***<br>(0.004)  |
| $\beta_2 + \beta_{32} + \beta_4 + \beta_{52}$                           | Business & Economics         | 0.061***<br>(0.004)  | 0.063***<br>(0.004)  | 0.057***<br>(0.007)  |
| $\beta_2 + \beta_{33} + \beta_4 + \beta_{53}$                           | Education                    | 0.018***<br>(0.005)  | 0.005<br>(0.008)     | 0.018***<br>(0.006)  |
| $\beta_2 + \beta_{34} + \beta_4 + \beta_{54}$                           | Engineering                  | 0.033***<br>(0.007)  | 0.029***<br>(0.008)  | 0.047***<br>(0.010)  |
| $\beta_2 + \beta_{35} + \beta_4 + \beta_{55}$                           | Math & Natural Sciences      | -0.004<br>(0.004)    | -0.004<br>(0.006)    | -0.009<br>(0.006)    |
| Observations                                                            |                              | 2,278,694            | 1,394,548            | 884,146              |

*Notes:* The dependent variable is log hourly wage. Panel A reports the estimated wage differences associated with global double majoring within each reported first-field category. Panel B reports the estimated wage differences associated with local double majoring within each reported first-field category. All specifications include individual controls, the state unemployment rate, graduation cohort fixed effects, and state fixed effects. Standard errors are clustered by graduation cohort and current state. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

## 1.6.2 Local and Global Double Majors

Table 1.5 displays the result of estimating Equation 1.2, which allows the returns to double-majoring to differ across global and local double-major combinations. Panel A reports wage differences for individuals with global combinations, defined as those whose second field lies outside of their reported first field’s broad category. Panel B reports the corresponding estimates for individuals with local combinations, defined as those whose two fields are within the same broad category.

Panel A shows that the association between global double majoring and wages differs substantially by first field. In the full sample, global double majoring is positively associated with wages for Humanities and Social Sciences and Education, but negatively associated with wages for Engineering and Math and Natural Sciences. The estimate for Business and Economics is also negative, but small and statistically insignificant. The contrast is especially clear for STEM first fields: workers whose first field is Engineering earn 3.8 percent less, and those whose first field is Math and Natural Sciences earn 3.0 percent less, than comparable single majors in the same first field when their second major is outside the same broad category. This heterogeneity is broadly consistent across highest degree education groups. The sign of the association is the same for bachelor’s-only workers and graduate-degree holders, with differences mainly in magnitude rather than direction.

Panel B shows a markedly different pattern for local double majors. In the full sample, local double majoring is positively associated with wages for Humanities and Social Sciences, Business and Economics, Education, and Engineering, while the estimate for Math and Natural Sciences is very small and statistically insignificant. The largest local premium appears for Business and Economics. The results by educational attainment show a broadly similar pattern, with differences mainly in magnitude and statistical significance rather than in the direction of the estimates.

Taken together, Tables 1.4 and 1.5 show that the wage association of double majoring

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<sup>17</sup>Figure A.2 shows the range of mean annual income across detailed fields within each broad field category.

<sup>18</sup>Table A.3 compares our estimates with the main results from studies that analyze the wage effects of double majoring relative to high- and low-income major benchmarks.

varies by both reported first field and the relationship between the two fields. Global combinations in Engineering and Math and Natural Sciences are associated with lower wages, suggesting possible opportunity costs when the reported first field is already linked to specialized, high-return labor-market pathways. Local combinations, by contrast, are more consistently associated with wage gains, especially in Business and Economics and Engineering.

### 1.6.3 Heterogeneity by Gender

These field-combination patterns are averages over workers who may differ in important ways. We next examine whether they vary by gender. Gender is relevant because field-of-study choices differ systematically by gender (Zafar, 2013), and these choices are closely linked to gender differences in occupational sorting and labor-market outcomes among college graduates (Sloane et al., 2021).

Table 1.6 examines whether the local and global double-major patterns differ by gender. Unlike Table 1.5, which separates the estimates by highest degree, this table uses the full sample and estimates the corresponding wage differences separately for women and men. Columns (2) and (3) report the gender-specific estimates, and column (4) reports the female–male difference in each coefficient.

Panel A shows that the negative wage differences associated with global STEM combinations are concentrated among women. For Engineering first majors, global double majoring is associated with lower wages for both women and men, but the penalty is substantially larger for women. For Math and Natural Sciences first majors, the estimate is large and negative for women, while the corresponding estimate for men is close to zero and statistically insignificant. In contrast, the female–male differences for global combinations in Humanities and Social Sciences, Business and Economics, and Education are small and statistically insignificant. These results suggest that the negative association between global double majoring and wages documented in Table 1.5 is largely, and in some cases entirely, concentrated

Table 1.6: Global and Local Effects of Double Majoring by Gender

| Parameter                                                               | First Field                  | Gender               |                      |                      |                      |
|-------------------------------------------------------------------------|------------------------------|----------------------|----------------------|----------------------|----------------------|
|                                                                         |                              | All<br>(1)           | Female<br>(2)        | Male<br>(3)          | Difference<br>(4)    |
| <i>Panel A. Global double-major wage differences within first field</i> |                              |                      |                      |                      |                      |
| $\beta_2$                                                               | Humanities & Social Sciences | 0.045***<br>(0.003)  | 0.047***<br>(0.004)  | 0.045***<br>(0.005)  | 0.001<br>(0.007)     |
| $\beta_2 + \beta_{32}$                                                  | Business & Economics         | -0.007<br>(0.005)    | -0.000<br>(0.006)    | -0.009<br>(0.006)    | 0.011<br>(0.008)     |
| $\beta_2 + \beta_{33}$                                                  | Education                    | 0.035***<br>(0.006)  | 0.035***<br>(0.007)  | 0.027**<br>(0.012)   | 0.011<br>(0.013)     |
| $\beta_2 + \beta_{34}$                                                  | Engineering                  | -0.038***<br>(0.006) | -0.062***<br>(0.012) | -0.026***<br>(0.007) | -0.034**<br>(0.014)  |
| $\beta_2 + \beta_{35}$                                                  | Math & Natural Sciences      | -0.030***<br>(0.005) | -0.062***<br>(0.006) | 0.006<br>(0.007)     | -0.065***<br>(0.009) |
| <i>Panel B. Local double-major wage differences within first field</i>  |                              |                      |                      |                      |                      |
| $\beta_2 + \beta_4$                                                     | Humanities & Social Sciences | 0.007***<br>(0.003)  | 0.017***<br>(0.003)  | -0.007*<br>(0.004)   | 0.026***<br>(0.005)  |
| $\beta_2 + \beta_{32} + \beta_4 + \beta_{52}$                           | Business & Economics         | 0.061***<br>(0.004)  | 0.065***<br>(0.005)  | 0.059***<br>(0.005)  | 0.009<br>(0.007)     |
| $\beta_2 + \beta_{33} + \beta_4 + \beta_{53}$                           | Education                    | 0.018***<br>(0.005)  | 0.028***<br>(0.005)  | -0.022**<br>(0.010)  | 0.054***<br>(0.011)  |
| $\beta_2 + \beta_{34} + \beta_4 + \beta_{54}$                           | Engineering                  | 0.033***<br>(0.007)  | 0.024<br>(0.018)     | 0.039***<br>(0.007)  | -0.014<br>(0.019)    |
| $\beta_2 + \beta_{35} + \beta_4 + \beta_{55}$                           | Math & Natural Sciences      | -0.004<br>(0.004)    | 0.006<br>(0.006)     | -0.011*<br>(0.006)   | 0.018**<br>(0.009)   |
| Observations                                                            |                              | 2,278,694            | 1,109,462            | 1,169,232            | 2,278,694            |

*Notes:* The dependent variable is log hourly wage. Panel A reports the estimated wage differences associated with global double majoring within each reported first-field category. Panel B reports the estimated wage differences associated with local double majoring within each reported first-field category. All specifications include individual controls, the state unemployment rate, graduation cohort fixed effects, and state fixed effects. Standard errors are clustered by graduation cohort and current state. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

among women.

Panel B shows that gender differences are not limited to global combinations. Local Business and Economics combinations are associated with sizable positive wage differences for both women and men, with little gender difference. However, in Humanities and Social Sciences and Education, local double majoring is associated with positive wage differences for women but negative or near-zero differences for men, producing statistically significant female–male gaps. For Engineering, the local estimate is positive and statistically signifi-

cant for men but smaller and imprecisely estimated for women. Unlike the negative wage associations for global double majoring, which are concentrated among women, the local estimates suggest that positive wage associations are more apparent among women in some fields, while negative or weaker associations are more often observed among men.

Overall, Table 1.6 shows that the wage associations of local and global double-major combinations differ by gender. The negative estimates for global STEM combinations are driven primarily by women, whereas the generally positive pattern for local combinations partly reflects positive estimates concentrated among women in some fields. These results indicate that the average patterns in Table 1.5 mask meaningful heterogeneity between women and men. To better understand this gender heterogeneity, The next section examines occupational choice and graduate education as potential channels.

## 1.7 Potential Mechanisms

The wage results show that individuals who choose global STEM double-major combinations, especially women, are associated with lower wages relative to comparable single majors. In contrast, local double-major combinations are generally associated with more favorable wage outcomes, with some of the positive associations concentrated among women. This section examines potential mechanisms that may help explain these patterns: graduate education and occupational sorting. Graduate education captures whether double-major combinations are associated with further human-capital accumulation after college. Occupational sorting is examined in two ways: whether graduates work in STEM-related occupations, and whether they work in occupations that match their first reported major.

### 1.7.1 Graduate Education

One possible channel linking double majoring to post-college wages is continued educational investment after the bachelor’s degree. As discussed above, one of the main reasons

students pursue double majors is to gain an advantage in the labor market. Graduate education can be understood in a similar way, since survey evidence suggests that students often view graduate education, especially master’s study, as an investment in career advancement, access to better jobs, and higher earnings (Wendler et al., 2012). In this sense, graduate study may reflect a continuation of the same labor-market-oriented educational strategy that motivates some students to pursue multiple undergraduate fields.

Graduate education is not homogeneous. The ACS distinguishes among bachelor’s, master’s, professional,<sup>19</sup> and doctoral degrees, which correspond to different training paths and labor-market outcomes. Table 1.7 illustrates this point by reporting mean hourly wages by first major and highest degree for all ages and separately for individuals aged 30 to 35.<sup>20</sup> The table shows that graduate education is not simply more schooling: the highest level of schooling is not always associated with the highest wage. Although doctoral degrees typically require the longest period of training, professional degrees are associated with higher mean wages in several fields. Thus, the type of graduate degree matters for understanding wage differences across undergraduate backgrounds.

To examine whether double majoring is associated with further schooling after the bachelor’s degree, we estimate linear probability models in which the dependent variables indicate whether the respondent’s highest degree is a master’s, professional, or doctoral degree. The specification follows Equation 1.2, with the same controls, fixed effects, and clustered standard errors used in the wage analysis. Table 1.8 reports the estimated associations separately for global and local double-major combinations within each reported first-field category.

Panel A shows that global double-major combinations are associated with different graduate-degree pathways across first fields. Business and Economics combinations are positively associated with all three degree types, while Math and Natural Sciences combinations are positively associated with master’s attainment but negatively associated with professional

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<sup>19</sup>Professional degrees include credentials such as J.D. in law, M.D. in medicine, and D.D.S. in dentistry. We follow the ACS educational attainment classification.

<sup>20</sup>We report the age 30–35 sample to approximate early labor-market outcomes after most individuals have completed their highest degree. The broad patterns by highest degree do not appear to differ substantially between the full sample and the age 30–35 sample.

Table 1.7: Hourly Wages by Major &amp; Degree

| ACS 2010–2019                           |                  |          |              |          |
|-----------------------------------------|------------------|----------|--------------|----------|
| First Major                             | Mean Hourly Wage |          |              |          |
|                                         | Bachelor’s       | Master’s | Professional | Doctoral |
| <b>Humanities &amp; Social Sciences</b> |                  |          |              |          |
| All Ages                                | 27.97            | 30.46    | 42.18        | 34.86    |
| Age 30–35                               | 23.63            | 25.29    | 35.69        | 28.94    |
| <b>Business &amp; Economics</b>         |                  |          |              |          |
| All Ages                                | 33.19            | 38.87    | 44.16        | 41.45    |
| Age 30–35                               | 28.35            | 33.15    | 37.91        | 35.96    |
| <b>Education</b>                        |                  |          |              |          |
| All Ages                                | 22.05            | 26.76    | 30.64        | 33.62    |
| Age 30–35                               | 18.61            | 22.71    | 25.19        | 26.87    |
| <b>Engineering</b>                      |                  |          |              |          |
| All Ages                                | 38.54            | 44.65    | 44.40        | 46.90    |
| Age 30–35                               | 32.22            | 36.76    | 36.44        | 38.18    |
| <b>Math &amp; Natural Sciences</b>      |                  |          |              |          |
| All Ages                                | 30.76            | 35.68    | 47.80        | 42.08    |
| Age 30–35                               | 25.49            | 30.04    | 37.88        | 35.40    |
| Degree Distribution                     | 63.09%           | 27.00%   | 6.43%        | 3.48%    |

*Notes:* The table reports mean hourly wages by first major and highest degree using ACS 2010–2019. The “All Ages” rows include all individuals in the analytic sample, while the “Age 30–35” rows restrict the sample to individuals aged 30 to 35. The final row reports the distribution of highest degree among individuals aged 30 to 35.

and doctoral degrees. Education shows the opposite pattern from Math and Natural Sciences, with a negative association with master’s degrees and positive associations with professional and doctoral degrees.

Panel B shows that local double-major combinations are more broadly associated with graduate-degree attainment. Humanities and Social Sciences, Education, and Math and Natural Sciences combinations are positively associated with all three degree types. Engineering is positively associated with master’s and doctoral attainment, while Business and Economics is positively associated with master’s and professional degrees but slightly negatively associated with doctoral attainment.

More importantly, these patterns indicate that graduate education can account for only part of the wage patterns documented above. The broadly positive associations for local double majors are consistent with their more favorable wage outcomes and may reflect ei-

Table 1.8: Double Majors and Post-Baccalaureate Highest Degree Attainment

| Parameter                                                           | First Field                  | Highest Degree       |                      |                      |
|---------------------------------------------------------------------|------------------------------|----------------------|----------------------|----------------------|
|                                                                     |                              | Master's<br>(1)      | Professional<br>(2)  | Doctoral<br>(3)      |
| <i>Panel A. Global double-major associations within first field</i> |                              |                      |                      |                      |
| $\beta_2$                                                           | Humanities & Social Sciences | 0.030***<br>(0.003)  | -0.000<br>(0.002)    | -0.001<br>(0.001)    |
| $\beta_2 + \beta_{32}$                                              | Business & Economics         | 0.064***<br>(0.003)  | 0.032***<br>(0.002)  | 0.016***<br>(0.001)  |
| $\beta_2 + \beta_{33}$                                              | Education                    | -0.021***<br>(0.007) | 0.011***<br>(0.003)  | 0.009***<br>(0.002)  |
| $\beta_2 + \beta_{34}$                                              | Engineering                  | 0.009*<br>(0.005)    | 0.010***<br>(0.002)  | 0.009***<br>(0.002)  |
| $\beta_2 + \beta_{35}$                                              | Math & Natural Sciences      | 0.055***<br>(0.004)  | -0.008***<br>(0.002) | -0.013***<br>(0.002) |
| <i>Panel B. Local double-major associations within first field</i>  |                              |                      |                      |                      |
| $\beta_2 + \beta_4$                                                 | Humanities & Social Sciences | 0.044***<br>(0.002)  | 0.039***<br>(0.002)  | 0.016***<br>(0.001)  |
| $\beta_2 + \beta_{32} + \beta_4 + \beta_{52}$                       | Business & Economics         | 0.016***<br>(0.003)  | 0.004***<br>(0.001)  | -0.002***<br>(0.001) |
| $\beta_2 + \beta_{33} + \beta_4 + \beta_{53}$                       | Education                    | 0.086***<br>(0.006)  | 0.011***<br>(0.003)  | 0.005**<br>(0.002)   |
| $\beta_2 + \beta_{34} + \beta_4 + \beta_{54}$                       | Engineering                  | 0.030***<br>(0.006)  | 0.001<br>(0.002)     | 0.014***<br>(0.002)  |
| $\beta_2 + \beta_{35} + \beta_4 + \beta_{55}$                       | Math & Natural Sciences      | 0.007*<br>(0.004)    | 0.032***<br>(0.003)  | 0.043***<br>(0.003)  |
| Observations                                                        |                              | 2,278,694            | 2,278,694            | 2,278,694            |

*Notes:* The dependent variables are indicators for whether the respondent's highest degree is a master's, professional, or doctoral degree. Panel A reports estimated associations between global double majoring and each type of post-baccalaureate degree within first-field categories. Panel B reports the corresponding associations for local double majoring. All specifications include individual controls, the state unemployment rate, graduation cohort fixed effects, and state fixed effects. Standard errors are clustered by graduation cohort and current state. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

ther human-capital accumulation within closely related fields that facilitates progression to higher levels of education or selection into local double-major combinations among students planning to pursue graduate education. However, several important wage patterns are not fully explained by graduate-degree attainment.

For example, Table 1.5 shows that local Business and Economics combinations have one of the largest wage premiums, but Table 1.8 shows that their graduate-degree associations are modest relative to other local combinations. Similarly, global STEM combinations are associated with lower wages in Table 1.5, even though global Engineering is positively associated with all three graduate-degree categories and global Math and Natural Sciences is positively associated with master’s attainment in Table 1.8. These discrepancies suggest that graduate education is not the primary channel behind the wage differences.

Furthermore, Appendix Tables A.4 and A.5 show that gender-specific graduate-degree patterns provide only partial support for the gender differences in wage outcomes. The clearest case is global Engineering: women with global Engineering combinations are less likely to attain a master’s degree and show no significant association with doctoral attainment, while men with the same type of combination are more likely to attain master’s, professional, and doctoral degrees. This pattern is consistent with the larger wage penalty observed among women in global Engineering. However, graduate education does not explain the gender difference for global Math and Natural Sciences, where women are more likely to attain master’s and professional degrees despite experiencing a larger wage penalty, while men are less likely to attain professional and doctoral degrees despite showing little wage penalty. Overall, these gender-specific results suggest that graduate education is a secondary mechanism and that additional mechanisms are needed to explain the gendered wage penalties among global STEM double majors.

### 1.7.2 STEM Occupations

Another potential mechanism is occupational sorting. The wage return to a college major depends not only on the field of study itself, but also on the types of occupations graduates enter after college. This channel is especially relevant for STEM fields because STEM-related occupations generally offer higher wages than many non-STEM occupations. If double-major combinations affect whether STEM graduates remain in STEM-related jobs or move into non-STEM jobs, they may help explain why some double-major combinations are associated with lower or higher wages.

We therefore examine whether double-major combinations are associated with employment in STEM-related occupations. The outcome is an indicator for whether the respondent works in a STEM-related occupation, defined using the 2018 Census occupation classification and the 2018 Standard Occupational Classification (SOC) system.<sup>21</sup> To estimate these associations, we use a linear probability model that follows Equation 1.2, replacing the wage outcome with the STEM-occupation indicator while retaining the same controls, fixed effects, and clustered standard errors used in the wage analysis. Table 1.9 reports the estimated associations separately for the full sample and by gender.

Panel A shows a sharp contrast between global double majors with non-STEM and STEM first fields. Global combinations are positively associated with STEM employment for Humanities and Social Sciences, Business and Economics, and Education first fields. In contrast, global combinations are negatively associated with STEM employment for Engineering and Math and Natural Sciences first fields. The decline is especially large for Math and Natural Sciences, and the female–male difference is substantial.

Panel B shows a different pattern for local double majors. Local Engineering combinations are positively associated with STEM employment for both women and men, consistent with related technical fields reinforcing STEM occupational pathways. By contrast, local combinations in non-STEM fields are generally associated with lower STEM employment.

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<sup>21</sup>The Census occupation classification is based on the 2018 SOC and consists of 570 specific occupation codes. See the U.S. Bureau of Labor Statistics 2018 SOC major groups: [https://www.bls.gov/soc/2018/major\\_groups.htm](https://www.bls.gov/soc/2018/major_groups.htm).

Table 1.9: Double Majors and Likelihood of Working in a STEM Occupation

| Parameter                                                           | First Field                  | STEM Occupation      |                      |                      |                      |
|---------------------------------------------------------------------|------------------------------|----------------------|----------------------|----------------------|----------------------|
|                                                                     |                              | All<br>(1)           | Female<br>(2)        | Male<br>(3)          | Difference<br>(4)    |
| <i>Panel A. Global double-major associations within first field</i> |                              |                      |                      |                      |                      |
| $\beta_2$                                                           | Humanities & Social Sciences | 0.101***<br>(0.003)  | 0.111***<br>(0.004)  | 0.089***<br>(0.004)  | 0.022***<br>(0.005)  |
| $\beta_2 + \beta_{32}$                                              | Business & Economics         | 0.085***<br>(0.003)  | 0.087***<br>(0.005)  | 0.085***<br>(0.005)  | 0.002<br>(0.006)     |
| $\beta_2 + \beta_{33}$                                              | Education                    | 0.096***<br>(0.005)  | 0.101***<br>(0.006)  | 0.082***<br>(0.008)  | 0.018*<br>(0.010)    |
| $\beta_2 + \beta_{34}$                                              | Engineering                  | -0.057***<br>(0.006) | -0.069***<br>(0.010) | -0.042***<br>(0.007) | -0.026**<br>(0.012)  |
| $\beta_2 + \beta_{35}$                                              | Math & Natural Sciences      | -0.157***<br>(0.004) | -0.221***<br>(0.006) | -0.067***<br>(0.006) | -0.155***<br>(0.008) |
| <i>Panel B. Local double-major associations within first field</i>  |                              |                      |                      |                      |                      |
| $\beta_2 + \beta_4$                                                 | Humanities & Social Sciences | -0.015***<br>(0.002) | -0.013***<br>(0.002) | -0.016***<br>(0.002) | 0.002<br>(0.003)     |
| $\beta_2 + \beta_{32} + \beta_4 + \beta_{52}$                       | Business & Economics         | -0.019***<br>(0.002) | -0.016***<br>(0.003) | -0.022***<br>(0.002) | 0.006*<br>(0.004)    |
| $\beta_2 + \beta_{33} + \beta_4 + \beta_{53}$                       | Education                    | -0.009***<br>(0.003) | -0.009***<br>(0.003) | -0.003<br>(0.007)    | -0.005<br>(0.007)    |
| $\beta_2 + \beta_{34} + \beta_4 + \beta_{54}$                       | Engineering                  | 0.061***<br>(0.007)  | 0.056***<br>(0.018)  | 0.058***<br>(0.007)  | -0.004<br>(0.020)    |
| $\beta_2 + \beta_{35} + \beta_4 + \beta_{55}$                       | Math & Natural Sciences      | -0.004<br>(0.004)    | -0.016***<br>(0.006) | 0.034***<br>(0.006)  | -0.051***<br>(0.008) |
| Observations                                                        |                              | 2,278,694            | 1,109,462            | 1,169,232            | 2,278,694            |

*Notes:* The dependent variable is an indicator for whether the respondent works in a STEM-related occupation. Panel A reports estimated associations between global double majoring and STEM occupation employment within each reported first-field category. Panel B reports the corresponding associations for local double majoring. Column (4) reports the estimated female–male difference in the association. All specifications include individual controls, the state unemployment rate, graduation cohort fixed effects, and state fixed effects. Standard errors are clustered by graduation cohort and current state. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

Local Math and Natural Sciences shows important gender heterogeneity: women are less likely to work in STEM occupations, while men are more likely to do so.

These results help explain the gender differences in the wage results, especially for global STEM combinations. Women with global Engineering and global Math and Natural Sciences combinations are significantly less likely than comparable men to work in STEM occupations. This pattern is consistent with the larger wage penalties observed among women in global STEM double majors. The evidence is particularly strong for Math and Natural Sciences, where the female–male gap in STEM employment is large.

At the same time, occupational sorting does not explain all of the wage patterns. For example, local Business and Economics combinations have large wage premiums even though they are not positively associated with STEM employment. Similarly, the gender wage differences shown in Table 1.5 are not fully explained by STEM occupational sorting. Most local combination patterns do not map onto wage differences. Thus, STEM occupational sorting appears to be an important mechanism for the gendered penalties among global STEM double majors, but additional mechanisms need to be examined.

### 1.7.3 Occupation Match

Another potential mechanism is the match between a graduate’s first major and current occupation. The wage return to a double major may depend not only on the fields combined, but also on whether graduates enter occupations that are closely related to their primary field of study. If some double-major combinations lead students away from occupations connected to their first major, this may help explain lower wage returns. Conversely, if other combinations strengthen the link between the first major and occupation, they may contribute to higher returns.

We therefore examine whether double-major combinations are associated with working in an occupation that matches the respondent’s first major. The outcome is an indicator for whether the respondent’s occupation is classified as matching the first reported major

field. We estimate a linear probability model that follows Equation 1.2, replacing the wage outcome with the first-major occupation match indicator while retaining the same controls, fixed effects, and clustered standard errors used in the wage analysis. Table 1.10 reports the estimated associations separately for the full sample and by gender. Because not all occupations are clearly related to a college field of study, we exclude occupations for which a major–occupation match is difficult to define. These include occupations such as police and military jobs, as well as clerical, manual, and other labor-intensive occupations that do not typically require a specific college major.

Panel A shows that global double majors are often associated with a lower likelihood of working in an occupation that matches the first major. The largest negative associations appear for Business and Economics and Engineering. Math and Natural Sciences also shows a negative association, though smaller in magnitude. There are some exceptions. Global double majors in Humanities and Social Sciences and Education are positively associated with first-major occupation match in the full sample. The Humanities and Social Sciences result is driven by women, while men show a negative association.

Panel B shows a different pattern for local double majors. Local combinations in Humanities and Social Sciences, Business and Economics, and Math and Natural Sciences are associated with higher first-major occupation match rates. This suggests that local double majors often reinforce occupational pathways related to the first major. Gender differences are also important. Local Engineering combinations increase first-major occupation match among women but decrease it among men. Local Math and Natural Sciences combinations are positive for both women and men, but the association is larger for women.

Overall, these results suggest that occupation match is one channel through which double majors may affect labor market outcomes. Global double majors, especially in Business and Economics and Engineering, appear more likely to move graduates away from occupations related to their first major. Local double majors, by contrast, are more likely to strengthen the connection between college major and occupation.

Compared with the wage results in Table 1.6, the occupation-match results suggest that

Table 1.10: Global and Local Effects of Double Majoring on First Major–Occupation Match by Gender

| Parameter                                                          | First Field                  | First Major–Occupation Match |                      |                      |                      |
|--------------------------------------------------------------------|------------------------------|------------------------------|----------------------|----------------------|----------------------|
|                                                                    |                              | All<br>(1)                   | Female<br>(2)        | Male<br>(3)          | Difference<br>(4)    |
| <i>Panel A. Global double-major differences within first field</i> |                              |                              |                      |                      |                      |
| $\beta_2$                                                          | Humanities & Social Sciences | 0.026***<br>(0.005)          | 0.060***<br>(0.006)  | -0.018***<br>(0.007) | 0.077***<br>(0.009)  |
| $\beta_2 + \beta_{32}$                                             | Business & Economics         | -0.188***<br>(0.005)         | -0.212***<br>(0.008) | -0.168***<br>(0.007) | -0.045***<br>(0.011) |
| $\beta_2 + \beta_{33}$                                             | Education                    | 0.012***<br>(0.003)          | 0.007**<br>(0.003)   | 0.022***<br>(0.007)  | -0.017**<br>(0.008)  |
| $\beta_2 + \beta_{34}$                                             | Engineering                  | -0.188***<br>(0.006)         | -0.135***<br>(0.010) | -0.188***<br>(0.007) | 0.052***<br>(0.012)  |
| $\beta_2 + \beta_{35}$                                             | Math & Natural Sciences      | -0.050***<br>(0.005)         | -0.048***<br>(0.006) | -0.058***<br>(0.007) | 0.009<br>(0.009)     |
| <i>Panel B. Local double-major differences within first field</i>  |                              |                              |                      |                      |                      |
| $\beta_2 + \beta_4$                                                | Humanities & Social Sciences | 0.041***<br>(0.003)          | 0.023***<br>(0.004)  | 0.062***<br>(0.005)  | -0.041***<br>(0.007) |
| $\beta_2 + \beta_{32} + \beta_4 + \beta_{52}$                      | Business & Economics         | 0.052***<br>(0.003)          | 0.052***<br>(0.005)  | 0.052***<br>(0.004)  | -0.002<br>(0.006)    |
| $\beta_2 + \beta_{33} + \beta_4 + \beta_{53}$                      | Education                    | -0.009***<br>(0.002)         | -0.006***<br>(0.002) | -0.012***<br>(0.004) | 0.002<br>(0.005)     |
| $\beta_2 + \beta_{34} + \beta_4 + \beta_{54}$                      | Engineering                  | -0.019**<br>(0.008)          | 0.054***<br>(0.021)  | -0.033***<br>(0.008) | 0.086***<br>(0.022)  |
| $\beta_2 + \beta_{35} + \beta_4 + \beta_{55}$                      | Math & Natural Sciences      | 0.075***<br>(0.006)          | 0.088***<br>(0.009)  | 0.051***<br>(0.008)  | 0.037***<br>(0.012)  |
| Observations                                                       |                              | 1,203,493                    | 595,827              | 607,666              | 1,203,493            |

*Notes:* The dependent variable is an indicator for whether the respondent works in an occupation that matches the first reported major field. Panel A reports the estimated differences associated with global double majoring within each reported first-field category. Panel B reports the estimated differences associated with local double majoring within each reported first-field category. Column (4) reports the estimated female–male difference. All specifications include the same individual controls, state unemployment rate, graduation cohort fixed effects, state fixed effects, and clustered standard errors used in the main wage analysis. Standard errors are clustered by graduation cohort and current state. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

first-major occupation match provides only a limited explanation for gender differences in wage returns. In particular, it does not explain the larger wage penalties for women in global STEM combinations. For global Engineering, women are actually less likely than men to move away from occupations matching the first major, and for global Math and Natural Sciences the female–male difference in occupation match is small and statistically insignificant.

At the same time, occupation match may help explain some of the female advantage in local double majors. This pattern is most consistent for local Math and Natural Sciences, where women have both a larger wage gain and a larger increase in first-major occupation match than men. Overall, first-major occupation match appears to be a partial mechanism for some local combinations, but not the main explanation for the gendered wage penalties among global STEM double majors.

Taken together, the mechanism results suggest that no single channel explains all of the wage patterns. Graduate education provides only a partial explanation, since several double-major combinations with higher graduate-degree attainment do not have higher wage returns. STEM occupational sorting provides the strongest evidence for the gendered penalties among global STEM double majors: women with global Engineering and Math and Natural Sciences combinations are especially likely to move away from STEM occupations. By contrast, first-major occupation match does not explain these global STEM penalties, although it may help explain some of the female advantage in local combinations, especially Math and Natural Sciences. Overall, the results suggest that global STEM penalties are more closely tied to sorting out of high-return STEM occupations, while some local advantages may operate through stronger links between college major, occupation, and further specialization.

## 1.8 Major Ordering

Understanding the ordering of the two majors is important because it determines the relevant comparison group for estimating the labor-market returns to double majoring. If the

reported first major captures the respondent’s primary human capital, then wage comparisons relative to the first major provide a natural baseline. If instead the ordering is random or follows another undisclosed rule, alternative specifications may be more appropriate.

Despite its importance, the ordering of majors has received little attention in the double-major literature, likely because of data limitations. Commonly-used datasets such as the NSCG and ACS distinguish between a first and second major, but they do not specify the rule by which respondents order them. Since these measures are survey-based, the reported first major may reflect the field respondents view as primary, the field most closely related to their current work, the field listed first on degree records, or an arbitrary rule.<sup>22</sup>

We therefore ask whether the ACS-reported ordering matters for the estimated wage patterns. Table 1.11 estimates Equation 1.1, with each column reassigning the first and second majors according to a different rule. Column (1) uses the ACS-reported order. Column (2) switches the first and second fields for double majors. Column (3) randomly assigns the order of the two fields. Column (4) assigns the higher-paying field as the first field. Together, these specifications indicate whether the estimated wage patterns are sensitive to the reported ordering of majors and help clarify what information, if any, is captured by the reported first field.

Panel A shows that changing the ordering rule does not alter the estimated wage premiums for single majors; this is true by construction. Panel B shows that the double-major estimates are more sensitive to the ordering rule. Column (2), which reverses the first and second majors for double majors, produces estimates that generally move in the same direction as those based on the reported order, but some magnitudes differ. Most notably, double majors whose second reported field is Engineering earn about 4 percent less than comparable single majors in Engineering, whereas the corresponding estimate in Column (1), for those who report Engineering as their first field, is only a 0.9 percent penalty. This pattern suggests that individuals who report Engineering as their second major differ systematically from those who report it first. Given that Engineering is the highest-paying field group on

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<sup>22</sup>We checked: it is not alphabetical.

Table 1.11: Alternative Major Ordering Rules

| Parameter                                                                                 | Field                        | Ordering Rule        |                      |                      |                           |
|-------------------------------------------------------------------------------------------|------------------------------|----------------------|----------------------|----------------------|---------------------------|
|                                                                                           |                              | Reported Order       | Switched             | Randomized           | Higher-Paying Field First |
|                                                                                           |                              | (1)                  | (2)                  | (3)                  | (4)                       |
| <i>Panel A. First-field wage differences relative to Humanities &amp; Social Sciences</i> |                              |                      |                      |                      |                           |
| $\beta_{12}$                                                                              | Business & Economics         | 0.157***<br>(0.002)  | 0.157***<br>(0.002)  | 0.157***<br>(0.002)  | 0.158***<br>(0.002)       |
| $\beta_{13}$                                                                              | Education                    | -0.106***<br>(0.002) | -0.107***<br>(0.002) | -0.106***<br>(0.002) | -0.107***<br>(0.002)      |
| $\beta_{14}$                                                                              | Engineering                  | 0.280***<br>(0.003)  | 0.280***<br>(0.003)  | 0.280***<br>(0.003)  | 0.280***<br>(0.003)       |
| $\beta_{15}$                                                                              | Math & Natural Sciences      | 0.166***<br>(0.002)  | 0.166***<br>(0.002)  | 0.166***<br>(0.002)  | 0.166***<br>(0.002)       |
| <i>Panel B. Double-major wage differences within first field</i>                          |                              |                      |                      |                      |                           |
| $\beta_2$                                                                                 | Humanities & Social Sciences | 0.020***<br>(0.002)  | 0.035***<br>(0.002)  | 0.029***<br>(0.002)  | -0.012***<br>(0.002)      |
| $\beta_2 + \beta_{32}$                                                                    | Business & Economics         | 0.034***<br>(0.003)  | 0.031***<br>(0.003)  | 0.031***<br>(0.003)  | 0.010***<br>(0.003)       |
| $\beta_2 + \beta_{33}$                                                                    | Education                    | 0.026***<br>(0.004)  | 0.012***<br>(0.003)  | 0.016***<br>(0.004)  | 0.018***<br>(0.005)       |
| $\beta_2 + \beta_{34}$                                                                    | Engineering                  | -0.009*<br>(0.005)   | -0.040***<br>(0.004) | -0.028***<br>(0.004) | -0.039***<br>(0.004)      |
| $\beta_2 + \beta_{35}$                                                                    | Math & Natural Sciences      | -0.017***<br>(0.003) | -0.014***<br>(0.003) | -0.014***<br>(0.003) | -0.042***<br>(0.003)      |
| Observations                                                                              |                              | 2,278,694            | 2,278,694            | 2,278,694            | 2,278,694                 |

*Notes:* The table reports estimates from Equation 1.1 under alternative rules for ordering the first and second majors. Column (1) uses the ACS-reported order. Column (2) switches the first and second fields for double majors. Column (3) randomly assigns the order of the two fields. Column (4) assigns the higher-paying field as the first field. Standard errors are reported in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

average, the result is consistent with the interpretation that the first reported major is more strongly associated with labor-market outcomes than the second reported major.

Similarly, Column (3), which randomly assigns the order of the two majors, preserves the same broad direction of the estimates as Column (2), but the magnitudes differ meaningfully for individuals assigned Education or Engineering as their first field. This pattern suggests that the first and second majors may not be interchangeable in their association with earnings. The differences are especially pronounced for Education and Engineering, the lowest- and highest-paying field groups on average, respectively, indicating that major ordering may matter most at the extremes of the field-specific wage distribution.

Next, Column (4) assigns whichever field belongs to the higher-paying group, among the five field groups, as the individual's first major. This ordering rule is similar in spirit to approaches used in prior studies that impose an ordering based on field-level returns rather than relying on the reported order (e.g., [Uddin and Tout, 2020](#); [Zhu and Zhang, 2021](#)). One interesting pattern is that when STEM fields, which have relatively high average labor-market earnings, are assigned as the first major, the estimated association between double majoring and earnings becomes more negative and larger in magnitude. The estimate for Humanities and Social Sciences also changes substantially. One possible explanation is that, under this rule, Humanities and Social Sciences is assigned as the first field mainly when it is paired with a lower-paying field such as Education, while cases in which it is paired with Business, Engineering, or Math and Natural Sciences are mechanically reassigned to those higher-paying fields.

These patterns appear to be a natural consequence of the assignment rule. Mechanically assigning the higher-paying field as the first major changes the composition of each first-field group and makes the second major systematically more likely to be lower-paying. This is especially important because higher-return fields such as Business and STEM may be chosen not only for earnings reasons but also for family expectations, perceived status, or parental approval ([Zafar, 2012](#)). Thus, mechanically reordering majors by field-level earnings may obscure the information contained in the reported order and create structural comparison

issues. The resulting estimates may therefore reflect the imposed ordering rule rather than the earnings association of double majoring itself.

Taken together, the alternative ordering rules do not reproduce the ACS-reported order, but they provide useful evidence that the two majors may not carry equivalent information. The first reported field appears to be more closely associated with earnings than the second reported field, especially for Education and Engineering, which lie at opposite ends of the average earnings distribution. For this reason, we view comparisons with single majors in the same first field as a preferable baseline for the main analysis relative to alternatives that ignore or mechanically reassign the reported ordering. Future work could further examine whether the reported ordering reflects the field most closely related to respondents' occupations, the field they regard as primary, or some other feature of their educational and labor-market trajectories.

## 1.9 Conclusion

This paper studies how the labor-market value of double majoring depends on the combination of fields. Using the 2010–2019 American Community Survey, we distinguish between local double majors, which combine fields within the same broad disciplinary area, and global double majors, which combine fields across broad disciplinary areas.

The results show that double majoring is not uniformly associated with higher earnings. Local combinations tend to generate positive wage premiums, consistent with complementarities between related fields. Global combinations produce more heterogeneous outcomes and are associated with wage penalties when the reported first field is in STEM. These penalties are concentrated among women and remain visible across age groups.

One interpretation is that field distance captures differences in the opportunity cost of academic breadth. When two fields are closely related, students may be able to complete both majors while preserving depth in a coherent skill domain. When fields are distant, the second major may broaden academic exposure but weaken the link between field-specific training and

occupational specialization. The occupational results support this interpretation: women with global STEM combinations are substantially less likely to work in STEM occupations than comparable STEM single majors despite holding STEM-related credentials.

These findings do not imply that global double majors are intrinsically undesirable. Students may choose distant fields for reasons not fully captured by wages, including preferences over job tasks, flexibility, non-pecuniary benefits, or preparation for interdisciplinary careers. A lower wage estimate may therefore reflect both labor-market penalties and deliberate choices over career paths. The results should instead be interpreted as evidence that the private wage return to double majoring depends on the structure of the field combination and the occupations into which graduates sort.

Several limitations are important. The ACS does not observe course-taking, grades, institutional quality, family background, or the reasons students choose a second major. It also records the order of fields as reported by respondents, but does not reveal whether the first field corresponds to chronological order, academic priority, or perceived identity. Our estimates should therefore be interpreted as descriptive associations rather than causal effects of double majoring. Nonetheless, the analysis using alternative ordering schemes suggests that reported order contains meaningful information, and the consistency of the wage and occupation results points to an economically relevant relationship between field combinations and labor-market outcomes.

The findings have practical implications for academic advising. Advising conversations often treat double majoring as a general enhancement to a student's educational portfolio. Our results suggest that the relevant question is not simply whether a student adds a second major, but which second major is added and how the combination maps into occupational pathways. Institutions may be able to improve the value of double majoring by helping students identify complementary field pairs, integrate requirements across departments, and understand the career implications of combining distant fields. Future research should examine how institutional policies, curricular integration, and advising practices shape the costs and benefits of double majoring.

# Chapter 2

## International Peer Effects in Doctoral Education

### 2.1 Introduction

The growing presence of international students in U.S. higher education has generated both optimism and concern. International students bring high-skilled talent to U.S. universities and help finance higher education through the resources they provide ([Bound et al., 2021](#)). At the same time, their growing presence has raised persistent concerns that foreign students may crowd out domestic students from graduate education ([Borjas, 2007](#)). Less attention, however, has been paid to how increases in international enrollment may affect international students themselves, especially in graduate programs where they already constitute a substantial share of the student population. These questions are particularly relevant in doctoral programs, where international students account for about 35 percent of all U.S. doctorate recipients and are heavily concentrated in science and engineering fields ([National Center for Science and Engineering Statistics, 2025b](#)). Yet we know little about what happens as international representation rises within doctoral cohorts: does the international composition of a cohort affect the academic performance, persistence, and degree

completion of both international and domestic students?

This paper addresses these questions using transcript-level administrative data from the Ohio Longitudinal Data Archive (OLDA), which include all doctoral students enrolled in Ohio public universities from 2005 to 2020. The main empirical challenge is that international students are not randomly distributed across programs: programs with more international students may differ in funding, research intensity, or selectivity from programs that admit or attract fewer international students. To address this concern, I define doctoral cohorts at the program-year level and exploit year-to-year fluctuations in international student representation within the same doctoral program, following cohort-composition designs in [Hoxby \(2000\)](#) and [Bostwick and Weinberg \(2022\)](#). I measure each student’s exposure to international peers as the share of international students among other students in the same entering cohort. Because this exposure may affect domestic and international students differently, I allow its effect to vary with each student’s own international status. I then examine effects on Ph.D. completion, dropout timing, and early academic performance.

I find that international peer composition does not affect average doctoral completion for either domestic or international students, but this aggregate null effect masks substantial heterogeneity. Separating programs by field shows no meaningful effect in STEM programs; in non-STEM programs, however, a higher share of international peers within the entering cohort lowers seven-year completion among international students, with no corresponding effect for domestic students. These results suggest that the relevance of international peer share depends importantly on field-specific training environments.

I next examine early GPA and the cumulative probability of dropping out by each program year to investigate potential mechanisms. In non-STEM fields, higher international peer exposure is associated with a small decline in early GPA among international students, but the magnitude is too small to account for the negative completion effect by itself. The cumulative attrition estimate increases most sharply between Years 2 and 3 only among international students in non-STEM fields. One possible explanation for this timing is that

some students wait to leave until they can receive an intermediate master’s degree.<sup>1</sup> In this case, difficulties may begin earlier in the program, but the observed dropout occurs later because students remain enrolled until they satisfy the master’s requirements. This would concentrate doctoral exits around the third year even if the underlying challenges arise before then.<sup>2</sup>

I also examine whether this relationship depends on how strongly international students are represented within the cohort. To do so, I augment the main model with a threshold term that allows the marginal effect of cohort international share to differ below and above the threshold, separately for domestic and international students. The results show that the negative association for international students is concentrated in lower-representation cohorts and disappears once international students become a larger presence in the entering cohort.

This paper makes three contributions to the literature on peer effects in higher education, particularly in doctoral education. First, to my knowledge, this is the first study to provide individual-level evidence on how the international peer composition of a doctoral cohort affects the academic outcomes of both domestic and international students. Whereas prior research focuses primarily on whether international enrollment displaces domestic students or changes aggregate degree completion, this study examines how changes in international representation within doctoral cohorts affect students after enrollment. Second, I use longitudinal transcript records from Ohio public universities that track doctoral students from entry through subsequent enrollment, grades, attrition, and degree completion. This structure allows me to observe when peer effects emerge and to distinguish weaker academic performance and attrition from delayed completion. Third, this study contributes to the peer-effects literature by showing that international peer effects in doctoral education vary by field and by the initial level of international representation within the cohort. This heterogeneity shifts the policy focus from limiting international enrollment to strengthening

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<sup>1</sup>Related qualitative research describes this pathway as “mastering out” (Maher et al., 2020).

<sup>2</sup>At The Ohio State University, students in several non-STEM doctoral programs can earn an en route master’s degree around the second year. Doctoral students typically earn an en route master’s during the second year in [history](#) and [English](#); in [sociology](#), the second-year paper may serve as the master’s thesis.

advising, academic integration, and peer support where negative effects emerge.

The remainder of this chapter is organized as follows. Section 2.2 reviews the related literature. Section 2.3 presents the conceptual framework for understanding how changes in the international-student share of a doctoral cohort may affect student outcomes. Section 2.4 describes the data and cohort construction. Section 2.5 explains the empirical strategy, identification assumption, and Monte Carlo simulation. Section 2.6 presents the results, including heterogeneity by field, program size, and international representation, as well as evidence on GPA and dropout timing. Section 2.7 concludes.

## 2.2 Related Literature

Recent studies provide evidence that a higher share of international peers can affect domestic students' undergraduate outcomes. Using administrative records from a research university, [Anelli et al. \(2023\)](#) exploit idiosyncratic variation in the share of foreign classmates in introductory math courses and find that foreign classmates reduce the likelihood that domestic students graduate with a STEM degree and work in a STEM occupation. They show that this displacement is concentrated in classes where foreign peers have weaker English proficiency, suggesting that communication frictions and reduced peer interaction may be important mechanisms. Similarly, [Luo \(2025\)](#) studies international student peer effects across ten selective public research universities in Texas and finds that a one-standard-deviation increase in the share of international classmates in introductory math courses lowers domestic students' course grades. The negative effects are especially pronounced among students at less selective institutions, where weaker academic preparation may make students more sensitive to competitive classroom environments.

Taken together, the undergraduate evidence suggests that exposure to international peers may generate negative effects for some domestic students, especially through competition and communication frictions. However, these findings cannot be directly generalized to graduate education. Most existing undergraduate studies identify peer exposure in introductory

courses, where interaction is tied to a single classroom. Graduate education, by contrast, is organized around repeated and sustained interaction within entering cohorts, seminars, laboratories, and research groups. International students also represent a much larger share of enrollment in many graduate programs than in undergraduate courses, making international cohort composition a potentially more central feature of the graduate training environment.

Despite these differences between undergraduate and graduate education, empirical evidence on international peer effects in graduate education remains limited. A few studies examine whether increases in international enrollment in U.S. graduate education affect degree completion among domestic students. Using a national-level panel dataset, [Zhang](#) finds that increases in foreign doctorate recipients in science and engineering are positively associated with the number of domestic doctorate recipients, suggesting no evidence that foreign students displace domestic degree production. Similarly, [Abegaz et al. \(2020\)](#) use university-by-discipline data and find that a larger number of international graduate degree recipients is associated with higher numbers of domestic graduate degree recipients and higher overall degree completion. Taken together, unlike the undergraduate literature, these graduate-level studies provide no evidence that international students reduce domestic students' degree production; if anything, they suggest that international and domestic graduate completion tend to move together positively.

These graduate-level studies provide an important foundation for understanding the relationship between international enrollment and graduate completion. However, they do not observe peer groups in the way they are experienced by doctoral students. Prior studies rely on broader university-, field-, or program-level measures of international enrollment and degree completion, and therefore cannot identify the international composition of a student's own entering cohort or follow individual students from entry through subsequent outcomes.

Building on this work, this study uses individual transcript records to define peers at the program-entry-cohort level. This allows me to measure each student's exposure to international peers as the share of international students among other students who entered the same doctoral program in the same year. I can therefore examine whether cohort com-

position affects doctoral progress after enrollment, separately for domestic and international students. The data also make it possible to study not only seven-year Ph.D. completion, but also early GPA, dropout timing, and whether the relationship varies across different levels of international representation within the cohort.

Although I refer to these relationships as international peer effects, the estimated effects may also partly capture broader cohort-composition channels. Changes in international representation may affect doctoral outcomes not only through direct student-to-student interactions, but also through resource or financial channels. For example, [Shih \(2017\)](#) shows that international graduate enrollment can increase domestic graduate enrollment through cross-subsidization, suggesting that international student presence may sometimes affect the resources available to students. This possibility should be kept in mind when interpreting the estimates below.

## 2.3 Conceptual Framework

Changes in the share of international students within a doctoral cohort may have either positive or negative effects on the academic outcomes of both domestic and international students. The direction of these effects likely reflects how changes in cohort composition<sup>3</sup> affect program resources, the academic environment, and interactions among students. This study therefore considers both potential negative effects arising from resource allocation and potential positive effects arising from academic and research complementarities.

First, an increase in the international student share may affect the demand for and allocation of program resources. Common resources in doctoral programs include faculty advising and financial support. International students may use these resources differently

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<sup>3</sup>Because the empirical specifications control for cohort size, changes in the international student share are interpreted as changes in cohort composition within cohorts of a given size. Thus, a higher international share corresponds to lower domestic representation, holding total cohort size fixed. This margin should not be interpreted as evidence that international students displace domestic students in admissions. Within-program fluctuations in the international share are not systematically related to cohort size; see [Figure 2.1](#). Nevertheless, both cohort size and international student representation exhibit broader trends over time; see [Appendix Figure B1](#).

from domestic students. For example, they may be more concentrated in particular research areas,<sup>4</sup> or they may rely more heavily on the subset of funding sources and assistantships for which they are eligible.<sup>5</sup> If program resources and funding systems do not adjust adequately to year-to-year changes in cohort composition, demand may become concentrated on particular resources, increasing competition among students who rely on those resources. This intensified competition may negatively affect international students, while domestic students may benefit if shifts in resource allocation reduce competition among domestic students for support and research opportunities.

Next, a higher share of international students may strengthen the academic and research environment within doctoral cohorts. International enrollment increases racial, linguistic, and cultural diversity and may bring together students with different academic preparation, prior research experience, specialized knowledge, and professional networks. Through these interactions, international peers may expand students' access to research ideas, information sources, and collaborative opportunities, benefiting both domestic and international students (Luo and Jamieson-Drake, 2013). However, greater cultural and linguistic diversity may not always generate positive peer effects. Prior work suggests that language and cultural differences can raise communication costs, and reduce academic outcomes (Anelli et al., 2023; Luo, 2025). Consistent with this concern, Chapter 3 shows, using related doctoral administrative data, that greater within-cohort linguistic distance is associated with lower Ph.D. completion for both domestic and international students. Thus, an increase in the international student share may combine both positive and negative peer effects, with the net association depending on whether the benefits of broader ideas, information, and networks outweigh the communication and integration costs.

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<sup>4</sup>This possibility is especially relevant within programs that have strong subfield specialization. Recent evidence from U.S. economics Ph.D. dissertations shows that field specialization varies by students' country or region of origin, suggesting that differences in field sorting may also be relevant when comparing domestic and international students within the same program (Singhal and Sierminska, 2025).

<sup>5</sup>Eligibility rules often differ by citizenship or immigration status. Although major federal fellowships such as NSF GRFP and NIH NRSA are not department-specific awards, their restrictions illustrate a broader point: university- or program-administered fellowships, training-grant slots, and assistantships may also be subject to eligibility rules tied to citizenship, residency, visa status, or sponsor-specific requirements (National Science Foundation, 2025; National Institutes of Health, 2026).

The relative importance of these positive and negative mechanisms may depend on the characteristics of doctoral programs. In large or highly structured programs, students may have access to multiple advisors, research groups, and peer networks. Such programs may also have a greater capacity to adjust resources and support systems in response to year-to-year changes in cohort composition. As a result, the composition of any single cohort may have a relatively limited effect on individual students. In smaller programs, by contrast, peer interactions are more concentrated, and each student constitutes a larger part of the available academic and social network. Changes in the international share may therefore have larger effects—whether positive or negative—on resource allocation, information flows, and social integration in smaller cohorts.

Effects may also vary across fields of study. Prior research documents substantial disciplinary differences in doctoral socialization and in the roles of faculty, peers, financial support, and informal information networks ([Gardner, 2007](#)). In many STEM programs, doctoral training is organized around laboratories, research teams, faculty grants, and research assistantships. Advisor-level resources and complementarities among members of a research team may therefore play particularly important roles in students’ academic progress. Non-STEM programs may rely more heavily on individual advising, departmental funding, and relatively informal research networks. These differences may shape how changes in cohort composition affect student outcomes through resource allocation and peer interaction. Consequently, average estimates for the full sample may conceal meaningful heterogeneity across fields.

The effects of international peer composition may also be nonlinear in the level of international representation within the cohort.<sup>6</sup> When international students are relatively few, they may have limited access to international peers who can provide information and support. As their representation increases, they may benefit from stronger peer networks and less isolation. At the same time, higher international representation may also create disad-

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<sup>6</sup>Because the empirical specifications include program fixed effects, “high” and “low” international representation refer to within-program variation across entering cohorts, not to differences between programs with persistently high or low international enrollment.

vantages if it leads to more segmented peer interactions or greater competition for resources used by international students. Thus, the marginal effect of international peer share may differ between low- and high-international-share cohorts and may be positive or negative depending on which mechanisms dominate.

Overall, this framework suggests that a higher international student share may generate both positive and negative effects on doctoral progress, and these effects may differ for domestic and international students. The empirical analysis therefore examines both the average effect of international peer share on academic progress and heterogeneity by student type, cohort size, field, and the initial level of international representation within the cohort.

## 2.4 Data

This study uses individual-level panel data from the Ohio Longitudinal Data Archive (OLDA).<sup>7</sup> The data include records for all students enrolled at Ohio’s public universities from Summer 2005 through Spring 2020 and contain term-by-term information on enrollment, academic programs, demographic characteristics, and degree attainment. I use these records to identify research doctoral students<sup>8</sup> at first enrollment and follow their academic progress, persistence, and degree attainment over time.

I define each doctoral program using the six-digit Classification of Instructional Programs (CIP) codes available in OLDA.<sup>9</sup> Programs are defined at the six-digit-CIP-by-institution

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<sup>7</sup>The Ohio Longitudinal Data Archive is a project of the Ohio Education Research Center ([oerc.osu.edu](https://oerc.osu.edu)) and provides researchers with centralized access to administrative data. The OLDA is managed by The Ohio State University’s CHRR ([chrr.osu.edu](https://chrr.osu.edu)) in collaboration with Ohio’s state workforce and education agencies ([olda.ohio.gov](https://olda.ohio.gov)), with those agencies providing oversight and funding. Further information about the sponsors is provided in the OLDA Acknowledgment section.

<sup>8</sup>Following the OLDA degree classification based on Ohio’s Higher Education Information (HEI) Degree/Certificate Earned (DC) file, I restrict the analytic sample to Doctor’s Degree–Research/Scholarship programs. I exclude Doctor’s Degree–Professional Practice programs, as well as programs classified as Doctor’s Degree–Other. See the Ohio Department of Higher Education’s HEI DC file documentation: <https://highered.ohio.gov/wps/portal/gov/odhe/data-reports/hei-system/hei-file-doc/hei-enrollment/hei-dc>.

<sup>9</sup>CIP is a standardized taxonomy of academic fields developed and maintained by the U.S. Department of Education’s National Center for Education Statistics. See <https://nces.ed.gov/ipeds/cipcode/>.

level,<sup>10</sup> so programs with the same CIP code at different universities are treated as distinct programs. A student’s entering cohort is determined by the first term of enrollment in that program.<sup>11</sup> Students who begin in the summer are assigned to the following fall cohort. This definition captures students who enter the same doctoral program at approximately the same time and therefore face a common initial peer environment.

I classify a student as international if the student is recorded in the administrative data as a nonresident alien. For each student  $i$  entering program  $p$  in year  $t$ , I construct the leave-one-out international-student share as

$$ShareInternational_{ipt} = \frac{\sum_{j \in \mathcal{C}_{pt}, j \neq i} International_j}{N_{pt} - 1}, \quad (2.1)$$

where  $\mathcal{C}_{pt}$  denotes the entering cohort in program  $p$  and year  $t$ , and  $N_{pt}$  is the total number of students in that cohort. The resulting measure captures the international composition of a student’s peers in the same six-digit-CIP-by-institution program-entry cohort. Excluding student  $i$  prevents the student’s own international status from mechanically determining the peer-composition measure.

The primary outcome is an indicator for whether a student completes a Ph.D. within seven years of initial enrollment. I also examine academic performance, measured by first-term and first-year GPA, and the timing of dropout. A student is classified as having dropped out by year seven if their enrollment records end within seven years of initial enrollment without a recorded doctoral degree.

I impose three principal sample restrictions. First, I retain students who entered their doctoral programs no later than Fall 2013. This restriction provides each entering cohort with a common seven-year follow-up period ending by Spring 2020 and limits exposure to pandemic-related disruptions at the end of the observation period. Second, I exclude students whose initial enrollment occurs in a spring or winter term because these off-cycle

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<sup>10</sup>See Table B1 for additional details on the field classification and program distribution.

<sup>11</sup>The administrative data distinguish four academic terms within each year: spring, summer, fall, and winter.

entrants cannot be assigned unambiguously to the fall-based entering cohorts. Third, I exclude programs with an average entering cohort size below five students, where averages are calculated across all observed cohorts within a program. Cohort composition measures are mechanically volatile in very small programs: the addition of a single international student, for example, can generate a large change in the measured international-student share. The resulting analytic sample contains 11,540 student-level observations from 129 Ph.D. programs at ten public universities.<sup>12</sup>

Table 2.1 describes the size and international composition of entering doctoral cohorts separately for STEM and non-STEM programs. The estimation sample consists of 1,071 program-entry cohorts, including 648 STEM cohorts and 423 non-STEM cohorts. STEM cohorts are modestly larger on average than non-STEM cohorts and contain substantially more international students. The average international-student share is 43 percent in STEM cohorts, compared with 16 percent in non-STEM cohorts, underscoring the stronger international presence in STEM doctoral programs.

Table 2.2 reports student-level summary statistics separately by international status. International students have a higher seven-year Ph.D. completion rate than domestic students (72 versus 59 percent) and a lower dropout rate by year 7 (20 versus 26 percent). Among students who complete a Ph.D., international students also finish somewhat more quickly, averaging 5.26 years compared with 5.48 years for domestic students.

The two groups also differ substantially in their observable characteristics. International students are younger at entry, less likely to be female, and considerably more likely to enroll in STEM fields. In particular, 83 percent of international students are enrolled in STEM programs, compared with 53 percent of domestic students. International students have slightly lower first-term and first-year GPAs, although the differences are small. These unconditional differences are descriptive and may partly reflect differences in the fields and programs in which international and domestic students enroll.

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<sup>12</sup>The universities are Bowling Green State University–Main Campus, Cleveland State University, Kent State University at Kent, Miami University–Oxford, Ohio State University–Main Campus, Ohio University–Main Campus, University of Akron Main Campus, University of Cincinnati–Main Campus, University of

Table 2.1: Cohort-Level Characteristics by Field, 2005–2013

| Variable                         | Mean        | SD   | Min | Max |
|----------------------------------|-------------|------|-----|-----|
| Panel A: STEM Programs           |             |      |     |     |
| Cohort size                      | 11.43       | 9.21 | 1   | 76  |
| Number of international students | 5.31        | 5.83 | 0   | 43  |
| Share international in cohort    | 0.43        | 0.29 | 0   | 1   |
| Observations                     | 648 cohorts |      |     |     |
| Panel B: Non-STEM Programs       |             |      |     |     |
| Cohort size                      | 9.83        | 9.61 | 1   | 77  |
| Number of international students | 1.66        | 2.64 | 0   | 23  |
| Share international in cohort    | 0.16        | 0.19 | 0   | 1   |
| Observations                     | 423 cohorts |      |     |     |

Notes: Statistics are calculated from entering cohorts in STEM and non-STEM doctoral programs between 2005 and 2013. The sample excludes programs with an average entering cohort size below five students, where averages are calculated across all observed cohorts within a program. Individual cohorts may therefore contain fewer than five students.

Table 2.2: Summary Statistics by International Status

|                                   | International<br>( $N = 4,143$ ) |           | Domestic<br>( $N = 7,397$ ) |           |
|-----------------------------------|----------------------------------|-----------|-----------------------------|-----------|
|                                   | Mean                             | Std. Dev. | Mean                        | Std. Dev. |
| Ph.D. completion within 7 years   | 0.72                             | 0.45      | 0.59                        | 0.49      |
| Still enrolled after 7 years      | 0.07                             | 0.25      | 0.14                        | 0.34      |
| Dropout by year 7                 | 0.20                             | 0.40      | 0.26                        | 0.44      |
| Years enrolled                    | 4.66                             | 1.89      | 4.70                        | 2.28      |
| Years to Ph.D. (graduates only)   | 5.26                             | 1.39      | 5.48                        | 1.62      |
| <i>Individual characteristics</i> |                                  |           |                             |           |
| Age at entry                      | 26.29                            | 4.03      | 28.61                       | 7.78      |
| Female                            | 0.40                             | 0.49      | 0.48                        | 0.50      |
| STEM                              | 0.83                             | 0.37      | 0.53                        | 0.50      |
| <i>Academic performance</i>       |                                  |           |                             |           |
| First-term GPA                    | 3.67                             | 0.41      | 3.73                        | 0.39      |
| First-year GPA                    | 3.69                             | 0.33      | 3.74                        | 0.33      |

Notes: The table reports student-level means and standard deviations. International status is based on the classification recorded in the administrative data. Years to Ph.D. is calculated only for students who completed a Ph.D. and is observed for 3,239 international students and 5,117 domestic students.

## 2.5 Empirical Strategy

I estimate a student-level linear probability model of Ph.D. completion within seven years, including program and entry-year fixed effects. The key regressors are the leave-one-out share of international students in a student’s program-entry cohort and its interaction with the student’s own international status. Following [Hoxby \(2000\)](#) and [Bostwick and Weinberg \(2022\)](#), the identifying variation arises from year-to-year fluctuations in cohort composition within doctoral programs, after accounting for common entry-cohort shocks and observed student and cohort characteristics. Specifically, I estimate:

$$\begin{aligned}
 Y_{ipt} = & \beta_1 \cdot \text{International}_i + \beta_2 \cdot \text{ShareInternational}_{ipt} \\
 & + \beta_3 \cdot (\text{International}_i \times \text{ShareInternational}_{ipt}) \\
 & + \gamma' \mathbf{X}_{ipt} + \delta' \mathbf{Z}_{pt} + D_p + D_t + \varepsilon_{ipt}.
 \end{aligned} \tag{2.2}$$

where  $Y_{ipt} = 1$  if student  $i$ , entering program  $p$  in year  $t$ , completes the Ph.D. within seven years. The vector of individual-level controls  $\mathbf{X}_{ipt}$  includes age, age-squared, race/ethnicity, and gender. Cohort-level controls  $\mathbf{Z}_{pt}$  include cohort size and the share of female students. All specifications include program fixed effects ( $D_p$ ) and entry-year fixed effects ( $D_t$ ).

The key variables are defined as follows.  $\text{International}_i$  is an indicator equal to one if student  $i$  is classified as an international student, defined as a nonresident alien without U.S. citizenship.  $\text{ShareInternational}_{ipt}$  denotes the fraction of international students in student  $i$ ’s entering cohort  $t$  of program  $p$ , excluding student  $i$  from the calculation. For ease of interpretation,  $\text{ShareInternational}_{ipt}$  and all peer-composition variables in the extended specifications are mean-centered at the overall sample average.<sup>13</sup> The interaction term captures whether international students are differentially affected by variation in the international composition of their entering cohort.

The coefficients are interpreted as follows.  $\beta_1$  captures the baseline difference in gradu-

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Toledo, and Wright State University–Main Campus.

<sup>13</sup>See [von Hippel and Schuetze \(2025\)](#) for a discussion of centering and interaction terms in linear models.

ation rates between international and domestic students.  $\beta_2$  measures how the graduation probability of domestic students changes as the share of international students in their cohort increases.  $\beta_3$  indicates whether international students are differentially affected by changes in their cohort’s international composition. The sum  $\beta_2 + \beta_3$  represents how the graduation probability of international students changes as the share of international students in their cohort increases.

The model is estimated using a linear probability model (LPM), which allows for a straightforward interpretation of the coefficients as marginal effects. Standard errors are clustered at the program level.<sup>14</sup> Therefore, I rely on the linear probability specification in the main analysis for its simplicity and ease of interpretation.

### 2.5.1 Identification Assumption

Identification comes from comparing cohorts within the same doctoral program that enter in different years with higher or lower international student shares. The key assumption is that, conditional on the control variables and fixed effects in Equation (2.2), deviations in a cohort’s international student share are unrelated to unobserved determinants of Ph.D. completion. In other words, a cohort with a relatively high international student share is compared to other cohorts in the same program, and the analysis assumes that those cohorts would have had similar completion outcomes in the absence of differences in international peer composition.

A potential concern is that a high-international-share cohort may differ from other cohorts in the same program for reasons beyond peer composition. For example, the program may admit more international students in a year when funding is strong or weak, admissions standards change, or the entering class differs in academic preparation. If these changes also

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<sup>14</sup>As a robustness check, I re-estimate the baseline completion model using a probit model and compare average marginal effects with the linear probability model estimates. The probit estimates are very similar in magnitude and statistical significance. The estimated effect of cohort international share is  $-0.038$  in both models, the interaction with international status is  $-0.024$  in the LPM and  $-0.021$  in the probit model, and the total effect for international students is  $-0.063$  in the LPM and  $-0.059$  in the probit model. None of these peer-composition estimates is statistically significant.

affect completion, the estimated relationship between international peer share and Ph.D. completion would not reflect peer composition alone, but would also capture these other cohort-level differences.

Although this assumption cannot be tested directly, I assess its plausibility indirectly by examining observable cohort characteristics. The concern is that changes in the international student share may coincide with other cohort-level changes, such as cohort size, average age, or gender composition. If so, the identifying variation would be correlated with observable composition, raising concerns that it may also be correlated with unobserved determinants of outcomes.

Figure 2.1 therefore examines whether within-program changes in the international student share are associated with these cohort characteristics. The figure provides no evidence of systematic relationships: the international student share is not meaningfully related to cohort size or gender composition. The only visible pattern is a weak negative relationship with average cohort age, but it is driven by a single outlier and disappears once that observation is excluded. Overall, these results suggest that variation in the international student share is not systematically related to observable cohort composition.

## 2.5.2 Monte Carlo Simulation

Following the approach of [Lavy and Schlosser \(2011\)](#), I use a Monte Carlo simulation to assess whether the within-program, across-cohort variation in international student shares is consistent with random variation that would arise given the observed cohort sizes and each program's average cohort international student share. The exercise provides a reference point for asking whether the cohort-to-cohort variation used in the empirical analysis is unusually large or small relative to what would be generated by this random process.

For each program  $p$  and entry cohort  $t$ , I use the observed cohort size,  $n_{pt}$ , and the program's average cohort international student share,  $\pi_p$ , as inputs to the simulation. In

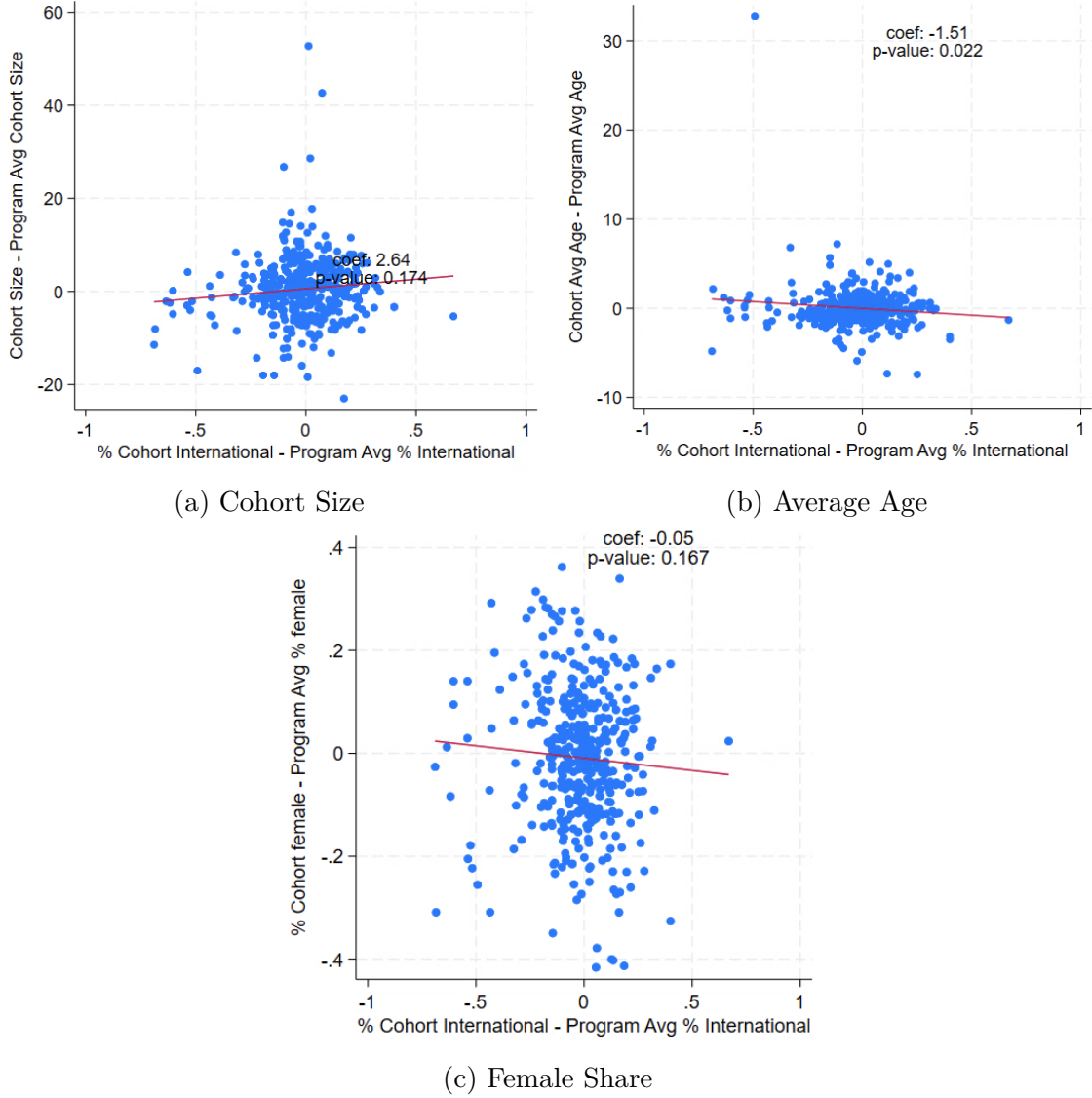


Figure 2.1: Correlation between cohort international composition and program-demeaned covariates. Panels display cohort size, average age, and female share. Reported lines are fitted values from regressions of each covariate on international share.

simulation  $s$ , the number of international students in that cohort,  $I_{pt}^s$ , is drawn as

$$I_{pt}^s \sim \text{Binomial}(n_{pt}, \pi_p).$$

I repeat this procedure 1,000 times for each program. For each simulated dataset, I calculate the standard deviation of the simulated cohort shares,  $I_{pt}^s/n_{pt}$ , across entry cohorts within the program. This produces, for each program, a distribution of 1,000 simulated standard

deviations. I use the 5th and 95th percentiles of this distribution to define the program’s 90% simulation interval.

I then compare each program’s observed standard deviation of cohort international shares with the program-specific 90% simulation interval. If the observed standard deviation falls within this interval, I consider the program’s cohort-to-cohort variation to be within the range expected under the random process described above. For 82.6% of programs, the observed standard deviation falls within the simulated 90% interval. This indicates that, for most programs, the extent of cohort-to-cohort variation in international student composition is consistent with what would be expected under the random process.

## 2.6 Results

Table 2.3: Effect of Cohort International Composition on Ph.D. Completion

| Parameter           | Variable / Effect                      | Ph.D. Completion within |                     |                     |
|---------------------|----------------------------------------|-------------------------|---------------------|---------------------|
|                     |                                        | 5 Years                 | 6 Years             | 7 Years             |
| $\beta_1$           | International student                  | 0.110***<br>(0.023)     | 0.124***<br>(0.026) | 0.131***<br>(0.025) |
| $\beta_2$           | Cohort international share             | 0.009<br>(0.035)        | -0.011<br>(0.036)   | -0.038<br>(0.037)   |
| $\beta_3$           | International $\times$ cohort share    | -0.078<br>(0.047)       | -0.027<br>(0.049)   | -0.024<br>(0.048)   |
| $\beta_2 + \beta_3$ | Total effect on international students | -0.069<br>(0.045)       | -0.038<br>(0.043)   | -0.063<br>(0.040)   |
| Observations        |                                        | 11,540                  | 11,540              | 11,540              |

*Notes:* Estimates are from linear probability models. The dependent variable is an indicator for completing the Ph.D. within 5, 6, or 7 years. All specifications include cohort size, age, age-squared, gender, cohort female share, race/ethnicity indicators, program fixed effects, and entry-year fixed effects. Standard errors are clustered at the programs level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table 2.3 reports estimates of how the international composition of entering cohorts affects the probability of completing a Ph.D. within alternative time horizons, based on model (1). Columns (1)–(3) present results for completion within five, six, and seven years, respectively. Across all completion horizons, the coefficient on the International indicator

( $\beta_1$ ) is positive and highly significant. International students are consistently more likely to complete the Ph.D. within the specified time frame than comparable domestic students.

By contrast, the coefficients on the cohort composition term ( $\beta_2$ ), its interaction with international status ( $\beta_3$ ), and the total effect for international students ( $\beta_2 + \beta_3$ ) are statistically indistinguishable from zero across all specifications. These results indicate that differences in Ph.D. completion are driven primarily by students' own international status, rather than by the share of international peers in their entering cohort.

Overall, variation in international student representation shows no statistically significant positive or negative effect on Ph.D. completion at any completion horizon. This null finding contrasts with common policy concerns about the expansion of international student enrollment, but aligns with prior research documenting no evidence of crowd-out effects associated with increases in international student supply.

One interpretation is that international peer effects may offset each other. As discussed in the conceptual framework, positive mechanisms, such as network support and peer learning, may coexist with negative mechanisms, including cultural or linguistic segmentation, leading to a net effect close to zero. An alternative explanation is that peer effects vary systematically across program characteristics, such as program size or field, and therefore average out in the aggregate. The next section examines these sources of heterogeneity in greater detail.

### 2.6.1 Heterogeneity by Field of Study

The effects of international peer composition may differ substantially across fields because doctoral training is organized differently in STEM and non-STEM programs. In many STEM fields, doctoral education is organized around laboratories, research teams, and faculty-led research projects ([National Academies of Sciences, Engineering, and Medicine, 2018](#)), making peer interaction and research-group membership central features of doctoral training. STEM students may also face greater exposure to international peers, given the concentration of international students in science and engineering doctoral education ([Bound et al., 2009](#)).

In many non-STEM fields, by contrast, doctoral training is less often organized around laboratory teams and more often relies on independent research, and individualized advising (Gardner, 2007). In these programs, international peer composition may operate through different channels, such as informal peer support and seminar and coursework interactions.<sup>15</sup> These differences suggest that aggregate estimates may conceal important heterogeneity in how international peer exposure shapes doctoral completion.

To examine whether these different channels translate into different completion outcomes, I extend Equation (2.2) by interacting a STEM indicator, equal to one for STEM programs and zero otherwise, with the international student indicator, the cohort international share, and their interaction. The resulting specification allows both the international–domestic completion gap and the marginal effect of international peer exposure to differ between STEM and non-STEM programs.

$$\begin{aligned}
Y_{ipt} = & \beta_1 \cdot \text{International}_i + \beta_2 \cdot \text{ShareInternational}_{pt} \\
& + \beta_3 \cdot (\text{International}_i \times \text{ShareInternational}_{pt}) \\
& + \beta_5 \cdot (\text{International}_i \times \text{STEM}_p) \\
& + \beta_6 \cdot (\text{ShareInternational}_{pt} \times \text{STEM}_p) \\
& + \beta_7 \cdot (\text{International}_i \times \text{ShareInternational}_{pt} \times \text{STEM}_p) \\
& + \boldsymbol{\gamma}'\mathbf{X}_{ipt} + \boldsymbol{\delta}'\mathbf{Z}_{pt} + D_p + D_t + \varepsilon_{ipt}.
\end{aligned} \tag{2.3}$$

In this specification,  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$  capture the corresponding effects for non-STEM programs. For STEM programs, the international–domestic completion gap is given by  $\beta_1 + \beta_5$ , the effect of cohort international share for domestic students is  $\beta_2 + \beta_6$ , and the additional effect of cohort international share for international students is  $\beta_3 + \beta_7$ . The total marginal effect of cohort international share for international students is therefore  $\beta_2 + \beta_3$

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<sup>15</sup>The American Academy of Arts and Sciences’ Humanities Indicators report that humanities and arts Ph.D. recipients spent a median of four years taking courses or preparing for exams, compared with two to three years in the natural science fields. See <https://www.amacad.org/humanities-indicators/higher-education/years-attainment-humanities-doctorate#32067>.

in non-STEM programs and  $\beta_2 + \beta_3 + \beta_6 + \beta_7$  in STEM programs.

Table 2.4 presents the results for Ph.D. completion within seven years. The estimated international-domestic completion gap is positive and statistically significant in both fields. Because the cohort international share is demeaned, the coefficients on the international-student indicator are interpreted at the average level of cohort international composition within each field. International students have a 14.0 percentage point higher completion probability than domestic students in non-STEM programs and an 11.9 percentage point higher probability in STEM programs.

The relationship between cohort international composition and completion differs substantially by field. In non-STEM programs, the cohort international share has a small and statistically insignificant association with completion among domestic students, while the interaction between international status and cohort international share is negative and statistically significant. The total marginal effect for international students,  $\beta_2 + \beta_3$ , is  $-0.208$  and is statistically significant at the 5 percent level. Because the standard deviation of cohort international share in non-STEM programs is 0.19, a one-standard-deviation increase is associated with an approximately 4.0 percentage point reduction in international students' probability of completing the Ph.D. within seven years, corresponding to a 7.1 percent decline relative to their mean completion rate of 56.1 percent.<sup>16</sup>

In STEM programs, the estimated effect of cohort international share on domestic students is negative but statistically insignificant, and its interaction with international status is small and also statistically insignificant. The resulting total marginal effect for international students,  $\beta_2 + \beta_3 + \beta_6 + \beta_7$ , is  $-0.043$  and cannot be distinguished from zero.

Overall, the results show that the negative association between international peer concentration and international students' timely completion is concentrated in non-STEM programs. One possible explanation is that communication and integration frictions become more consequential in fields characterized by language-intensive instruction and less struc-

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<sup>16</sup>For comparison, the mean seven-year completion rate among international students in STEM programs is 68.4 percent.

Table 2.4: Effect of Cohort International Composition on Ph.D. Completion within 7 Years: Heterogeneity by Field of Study

| Parameter                               | Variable / Effect                           | Ph.D. Completion<br>within 7 Years |
|-----------------------------------------|---------------------------------------------|------------------------------------|
| <b>Panel A. Non-STEM programs</b>       |                                             |                                    |
| $\beta_1$                               | International student                       | 0.140***<br>(0.030)                |
| $\beta_2$                               | Effect on domestic students                 | 0.019<br>(0.074)                   |
| $\beta_3$                               | Additional effect on international students | -0.227**<br>(0.095)                |
| $\beta_2 + \beta_3$                     | Effect on international students            | -0.208**<br>(0.088)                |
| $\Delta_1 \text{ SD}$                   | +1 SD effect on international students      | [-0.040]                           |
| <b>Panel B. STEM programs</b>           |                                             |                                    |
| $\beta_1 + \beta_5$                     | International student                       | 0.119***<br>(0.016)                |
| $\beta_2 + \beta_6$                     | Effect on domestic students                 | -0.060<br>(0.042)                  |
| $\beta_3 + \beta_7$                     | Additional effect on international students | 0.018<br>(0.053)                   |
| $\beta_2 + \beta_3 + \beta_6 + \beta_7$ | Effect on international students            | -0.043<br>(0.045)                  |
| $\Delta_1 \text{ SD}$                   | +1 SD effect on international students      | [-0.012]                           |
| Observations                            |                                             | 11,540                             |

*Notes:* The dependent variable is an indicator for completing the Ph.D. within seven years. The reported coefficients are linear combinations from a model interacting international student status, cohort international share, and the STEM indicator. Panel A reports effects for non-STEM programs ( $STEM = 0$ ), and Panel B reports effects for STEM programs ( $STEM = 1$ ). For cohort international share, the coefficient labeled “Effect on domestic students” reports the marginal effect for domestic students, while “Effect on international students” reports the corresponding marginal effect for international students. The effect of a +1 SD increase is calculated by multiplying the group-specific marginal effect by the field-specific standard deviation of cohort international share. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

tured peer collaboration. The estimates do not, however, directly identify these mechanisms. More broadly, the findings demonstrate that the relationship between international cohort composition and doctoral completion depends importantly on disciplinary context.

### 2.6.2 Heterogeneity by Program Size

I next examine whether the effect of international peers varies with the average cohort size of the program. The same international-student share can imply very different numbers of international peers across programs of different sizes. For example, in a program with an average cohort size of 10 students, a 10-percentage-point increase in the international share corresponds to one additional international peer, whereas in a program with an average cohort size of 30 students, the same increase corresponds to three additional international peers. Program size may also shape how peer effects operate: students in larger programs may have broader academic and social networks, while changes in subgroup composition may more sharply affect peer environments in smaller programs.

Figure 2.2 shows that average cohort size varies substantially across programs. The mean program-level average cohort size is 10.4 students ( $SD = 7.9$ ), while the distribution is concentrated near five students and extends up to 63 students. I examine heterogeneity using three alternative definitions of small and large programs: a median cutoff (7.83 students), a mean cutoff (10.4 students), and a bottom/top tercile comparison that excludes programs in the middle tercile.

Table 2.5 summarizes program-level characteristics under these definitions. The table shows that program size differences mainly translate into differences in the number of international peers, rather than large differences in international-student shares. Across the three definitions, large programs have roughly three times as many international students per cohort as small programs, while average international-student shares remain relatively similar across groups. Large programs are also more likely to be STEM programs.

Table 2.6 reports heterogeneous effects of international peer composition on Ph.D. com-

Table 2.5: Program-Level Characteristics by Program Size

| Variable                                 | Program-Size Definition |       |             |       |                |       |
|------------------------------------------|-------------------------|-------|-------------|-------|----------------|-------|
|                                          | Median cutoff           |       | Mean cutoff |       | Bottom/Top 33% |       |
|                                          | Mean                    | SD    | Mean        | SD    | Mean           | SD    |
| Panel A: Large Programs                  |                         |       |             |       |                |       |
| Average cohort size                      | 17.37                   | 10.49 | 21.96       | 11.64 | 20.73          | 11.45 |
| Average number of international students | 6.51                    | 6.56  | 8.65        | 7.20  | 8.44           | 7.23  |
| Average international share              | 0.36                    | 0.24  | 0.39        | 0.23  | 0.40           | 0.25  |
| STEM                                     | 0.63                    | 0.49  | 0.69        | 0.47  | 0.72           | 0.45  |
| Programs                                 | 65                      |       | 36          |       | 43             |       |
| Panel B: Small Programs                  |                         |       |             |       |                |       |
| Average cohort size                      | 8.04                    | 3.22  | 9.17        | 4.06  | 7.19           | 1.68  |
| Average number of international students | 2.61                    | 2.08  | 3.00        | 3.09  | 2.20           | 1.96  |
| Average international share              | 0.33                    | 0.23  | 0.33        | 0.24  | 0.30           | 0.23  |
| STEM                                     | 0.58                    | 0.50  | 0.57        | 0.50  | 0.51           | 0.51  |
| Programs                                 | 64                      |       | 93          |       | 43             |       |

Notes: Statistics are calculated at the program level. Program size is defined using the program-level average cohort size. The table reports characteristics separately for small and large programs under three alternative definitions: median cutoff, mean cutoff, and bottom/top tercile comparison. For the bottom/top tercile comparison, programs in the middle tercile are excluded.

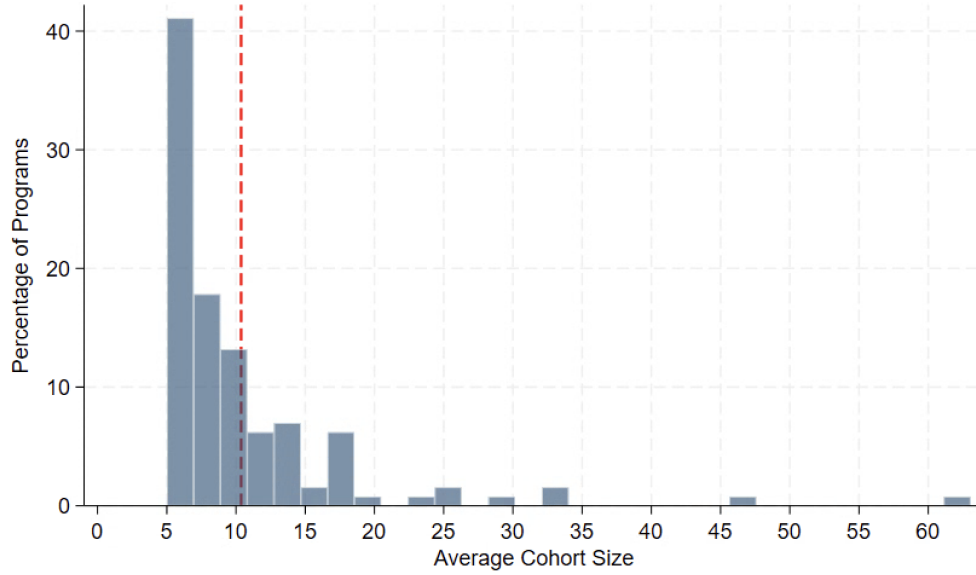


Figure 2.2: Distribution of Average Cohort Size Across Programs

*Notes:* The red dashed vertical line indicates the mean program-level average cohort size, 10.4 students.

pletion within seven years by program size. To estimate these effects, I use the same interaction structure as in Equation (2.3), replacing the STEM indicator with an indicator for small programs. Across all three definitions of program size, international students have higher completion probabilities than comparable domestic students in both large and small programs, consistent with the baseline estimates. The estimated international-student advantage ranges from 12.1 to 13.1 percentage points in large programs and from 11.0 to 12.7 percentage points in small programs.

The estimates provide no evidence that the effect of cohort international composition varies systematically by program size. For domestic students, the estimated effect of cohort international share is statistically insignificant in every specification, for both large and small programs. The interaction between international status and cohort international share is also statistically insignificant across all program-size definitions. As a result, the total marginal effect of cohort international share for international students is negative in both large and small programs, but not statistically distinguishable from zero. These results suggest that the negative relationship between international peer concentration and timely completion is not meaningfully moderated by program size. They further indicate that the stronger

Table 2.6: Effect of Cohort International Composition on Ph.D. Completion within 7 Years: Heterogeneity by Program Size

| Parameter                               | Variable / Effect                      | Ph.D. Completion within 7 Years |                     |                     |
|-----------------------------------------|----------------------------------------|---------------------------------|---------------------|---------------------|
|                                         |                                        | Median cutoff                   | Mean cutoff         | Bottom/Top 33%      |
| Panel A. Large programs                 |                                        |                                 |                     |                     |
| $\beta_1$                               | International student                  | 0.121***<br>(0.016)             | 0.131***<br>(0.018) | 0.123***<br>(0.018) |
| $\beta_2$                               | Cohort international share             | -0.070<br>(0.052)               | -0.071<br>(0.067)   | -0.085<br>(0.062)   |
| $\beta_3$                               | International $\times$ cohort share    | 0.007<br>(0.060)                | -0.012<br>(0.074)   | -0.005<br>(0.070)   |
| $\beta_2 + \beta_3$                     | Total effect on international students | -0.063<br>(0.052)               | -0.083<br>(0.062)   | -0.091<br>(0.058)   |
| Panel B. Small programs                 |                                        |                                 |                     |                     |
| $\beta_1 + \beta_5$                     | International student                  | 0.127***<br>(0.026)             | 0.114***<br>(0.021) | 0.110***<br>(0.038) |
| $\beta_2 + \beta_6$                     | Cohort international share             | 0.014<br>(0.051)                | -0.017<br>(0.044)   | -0.049<br>(0.061)   |
| $\beta_3 + \beta_7$                     | International $\times$ cohort share    | -0.085<br>(0.076)               | -0.037<br>(0.063)   | -0.043<br>(0.109)   |
| $\beta_2 + \beta_3 + \beta_6 + \beta_7$ | Total effect on international students | -0.071<br>(0.062)               | -0.054<br>(0.052)   | -0.092<br>(0.089)   |
| Observations                            |                                        | 11,540                          | 11,540              | 8,580               |

*Notes:* The dependent variable is an indicator for completing the Ph.D. within seven years. Each column reports estimates from a separate specification defining small and large programs using the median cutoff, mean cutoff, or bottom/top tercile cutoff. The reported coefficients are linear combinations from a model interacting international student status, cohort international share, and the small program indicator. Panel A reports effects for large programs (*SmallProgram* = 0), and Panel B reports effects for small programs (*SmallProgram* = 1). The row “Total effect on international students” reports the marginal effect of cohort international share for international students. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

negative association observed in non-STEM fields is unlikely to be driven simply by the smaller average size of non-STEM programs.

### 2.6.3 Nonlinearity Analysis

I next examine whether the relationship between international peer exposure and Ph.D. completion is nonlinear. The baseline and heterogeneity specifications estimate an average marginal effect of cohort international share, implicitly assuming that a 10-percentage-point increase has the same association with completion regardless of the baseline level of international representation. This assumption may fail to capture important differences in peer

dynamics across cohorts with low versus high levels of international representation. A change from very low to moderate international representation may have different implications than a change from already high to even higher representation. Theoretically, this possibility is consistent with work on tokenism and critical mass. Work on tokenism suggests that when minority members are relatively few, they may become more visible as tokens and face stronger pressure to adapt to dominant group norms (Kanter, 1977). Applied to this context, international students in cohorts with low international representation may have stronger incentives to integrate with domestic peers and adapt to existing program norms, while also having limited access to international-student peer support. As their representation increases, cohorts may reach a form of critical mass, where the size of the minority group becomes large enough to alter patterns of interaction, information exchange, and group formation (Oliver et al., 1985). These changes may provide international students with academic support, information sharing, and social belonging. At higher levels, however, larger international peer networks may also produce more segmented patterns of interaction between domestic and international students. These competing mechanisms suggest that the association between cohort international share and Ph.D. completion may vary across the distribution of international representation rather than following a single linear pattern.

To allow for such nonlinearities, I extend Equation (2.2) by introducing a linear spline in cohort international share. The spline allows the marginal association between international peer exposure and Ph.D. completion to differ below and above a threshold (or knot),  $\kappa$ :

$$\begin{aligned}
Y_{ipt} = & \beta_1 \cdot \text{International}_i + \beta_2 \cdot \text{ShareInternational}_{ipt} + \beta_3 \cdot (\text{ShareInternational}_{ipt} - \kappa)_+ \\
& + \beta_4 \cdot (\text{International}_i \times \text{ShareInternational}_{ipt}) \\
& + \beta_5 \cdot [\text{International}_i \times (\text{ShareInternational}_{ipt} - \kappa)_+] \\
& + \gamma' \mathbf{X}_{ipt} + \delta' \mathbf{Z}_{pt} + D_p + D_t + \varepsilon_{ipt}.
\end{aligned} \tag{2.4}$$

Here,  $(\text{ShareInternational}_{ipt} - \kappa)_+$  equals zero below the knot and equals

$ShareInternational_{ipt} - \kappa$  above the knot. For domestic students, the marginal effect of cohort international share is  $\beta_2$  below the knot and  $\beta_2 + \beta_3$  above the knot. For international students, the corresponding marginal effects are  $\beta_2 + \beta_4$  and  $\beta_2 + \beta_3 + \beta_4 + \beta_5$ .

The preferred specification sets the knot at 35 percent international representation, motivated by the idea that group dynamics may change once international students become a sizable minority rather than only a small presence in the cohort (Kanter, 1977).<sup>17</sup> I also consider two alternative knots: 20 percent, which corresponds roughly to one international student in a cohort of five students and therefore captures a low-representation threshold, and 50 percent, where international students approach numerical parity with domestic students.<sup>18</sup> These alternative thresholds assess whether the estimated nonlinear pattern is sensitive to the choice of cutoff. Table 2.7 reports cohort-level summary statistics separately for cohorts at or below and above each threshold. Cohort size does not differ substantially across the threshold splits, but cohorts above the knots are much more likely to be in STEM fields.

Table 2.8 reports estimates from the spline specification in Equation (2.4). For domestic students, the implied marginal effects of cohort international share are small and statistically insignificant across all three knot choices. In the preferred 35 percent specification, the domestic-student slope is  $-0.032$  below the knot and  $-0.128$  above the knot, neither of which is statistically distinguishable from zero.

For international students, the pattern is different. Below the knot, the marginal effect of cohort international share is negative across all three specifications. In the preferred 35 percent specification, the estimate is  $-0.086$  and statistically significant at the 10 percent level. The estimates are similar in sign under the 20 percent and 50 percent knots, with magnitudes of  $-0.126$  and  $-0.084$ , respectively. Scaling these effects by a one-standard-deviation increase in cohort international share below each knot implies declines in seven-

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<sup>17</sup>Kanter characterizes a 65:35 composition as a setting in which minority members are numerous enough to form alliances and potentially affect group culture.

<sup>18</sup>I do not use the sample mean as an alternative knot because the mean cohort international share is approximately 36 percent, nearly identical to the preferred 35 percent cutoff, and therefore does not provide a distinct robustness benchmark.

Table 2.7: Cohort-Level Characteristics by International-Share Threshold

| Variable                                     | International-Share Threshold |      |          |      |          |      |
|----------------------------------------------|-------------------------------|------|----------|------|----------|------|
|                                              | 20% knot                      |      | 35% knot |      | 50% knot |      |
|                                              | Mean                          | SD   | Mean     | SD   | Mean     | SD   |
| <b>Panel A: Cohorts at or below the knot</b> |                               |      |          |      |          |      |
| Cohort size                                  | 10.59                         | 8.68 | 10.75    | 9.61 | 10.58    | 9.56 |
| Number of international students             | 0.78                          | 1.37 | 1.54     | 2.35 | 2.16     | 3.10 |
| International share                          | 0.06                          | 0.07 | 0.13     | 0.12 | 0.20     | 0.17 |
| STEM                                         | 0.35                          | 0.48 | 0.42     | 0.49 | 0.48     | 0.50 |
| Cohorts                                      | 389                           |      | 600      |      | 759      |      |
| Students                                     | 4,119                         |      | 6,447    |      | 8,033    |      |
| <b>Panel B: Cohorts above the knot</b>       |                               |      |          |      |          |      |
| Cohort size                                  | 11.35                         | 9.78 | 11.50    | 9.07 | 12.35    | 8.80 |
| Number of international students             | 5.87                          | 5.66 | 7.27     | 6.07 | 8.83     | 6.37 |
| International share                          | 0.51                          | 0.22 | 0.63     | 0.17 | 0.73     | 0.13 |
| STEM                                         | 0.76                          | 0.43 | 0.86     | 0.34 | 0.93     | 0.26 |
| Cohorts                                      | 654                           |      | 443      |      | 284      |      |
| Students                                     | 7,421                         |      | 5,093    |      | 3,507    |      |

Notes: Statistics are calculated at the cohort level, where a cohort is defined by program and entering year. Cohorts are classified according to whether their cohort international share is at or below, or above, each threshold. Student-level outcomes are averaged within cohorts before calculating cohort-level means. The 20 percent threshold corresponds roughly to one international student in a cohort of five students, the 35 percent threshold is the preferred specification, and the 50 percent threshold corresponds to approximate numerical parity.

year completion of 0.9, 1.0, and 1.4 percentage points under the 20, 35, and 50 percent knots, respectively. Above the knot, however, the estimated marginal effects for international students become small or positive and are statistically insignificant.

Overall, the results provide evidence that the association between international peer exposure and completion differs across low- and high-representation cohorts. The negative international peer effect for international students appears concentrated below the knot, while there is no evidence of a negative relationship once international students constitute a significant share of the cohort. This pattern aligns with the theoretical expectation that

Table 2.8: Effect of Cohort International Composition on Ph.D. Completion within 7 Years: Nonlinearity by International Share

|                                                         |                                          | Ph.D. Completion within 7 Years |                     |                     |
|---------------------------------------------------------|------------------------------------------|---------------------------------|---------------------|---------------------|
| Parameter                                               | Variable / Effect                        | 20% knot                        | 35% knot            | 50% knot            |
| Panel A. Estimated coefficients                         |                                          |                                 |                     |                     |
| $\beta_1$                                               | International student                    | 0.116***<br>(0.015)             | 0.120***<br>(0.015) | 0.121***<br>(0.015) |
| $\beta_2$                                               | Cohort international share               | -0.042<br>(0.054)               | -0.032<br>(0.044)   | -0.037<br>(0.040)   |
| $\beta_3$                                               | Above-knot spline                        | 0.008<br>(0.129)                | -0.097<br>(0.193)   | -0.224<br>(0.448)   |
| $\beta_4$                                               | International $\times$ cohort share      | -0.084<br>(0.066)               | -0.055<br>(0.053)   | -0.048<br>(0.049)   |
| $\beta_5$                                               | International $\times$ above-knot spline | 0.171<br>(0.166)                | 0.227<br>(0.240)    | 0.680<br>(0.505)    |
| Panel B. Marginal effects of cohort international share |                                          |                                 |                     |                     |
| $\beta_2$                                               | Domestic students, below knot            | -0.042<br>(0.054)               | -0.032<br>(0.044)   | -0.037<br>(0.040)   |
| $\beta_2 + \beta_3$                                     | Domestic students, above knot            | -0.050<br>(0.097)               | -0.128<br>(0.173)   | -0.261<br>(0.435)   |
| $\beta_2 + \beta_4$                                     | International students, below knot       | -0.126**<br>(0.057)             | -0.086*<br>(0.045)  | -0.084**<br>(0.042) |
| $\Delta_1$ SD                                           | Effect of +1 SD                          | [-0.009]                        | [-0.010]            | [-0.014]            |
| $\beta_2 + \beta_3 + \beta_4 + \beta_5$                 | International students, above knot       | 0.037<br>(0.083)                | 0.044<br>(0.136)    | 0.372<br>(0.270)    |
| Observations                                            |                                          | 11,540                          | 11,540              | 11,540              |

*Notes:* The dependent variable is an indicator for completing the Ph.D. within seven years. Each column reports estimates from a separate linear spline specification with a different knot in cohort international share. The 35 percent knot is the preferred specification. The 20 percent knot corresponds roughly to one international student in a cohort of five students and captures a low-representation threshold, while the 50 percent knot corresponds to approximate numerical parity. The above-knot spline is defined as  $(\text{ShareInternational}_{ipt} - \kappa)_+$ . Panel B reports linear combinations corresponding to the marginal effect of cohort international share below and above the knot for domestic and international students. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

the international peer effect may vary across the distribution of international representation. The estimates suggest that the negative international peer effect is concentrated before international students reach critical mass, whereas the association weakens beyond that point. At the same time, the above-knot spline terms are not statistically significant.

## 2.6.4 Potential Mechanisms

This section investigates the mechanisms underlying the negative international peer effects documented above, which are concentrated in non-STEM fields and in cohorts with low baseline international-student shares. I examine whether changes in the presence of international students affect academic outcomes prior to degree completion, including grade point average (GPA) and dropout timing. By focusing on these intermediate outcomes, the analysis provides empirical evidence on within-program international peer effects during the Ph.D. training period, a dimension that has not yet been established in the graduate education literature.

### Grades

I first examine academic performance as a potential mechanism linking international peer composition to Ph.D. completion. If higher international peer exposure affects students' progress during training, one channel through which this may occur is weaker short-run academic performance. Higher international peer concentration may weaken academic performance if it leads to more segmented peer networks, reducing access to domestic peers who are more familiar with local academic norms, institutional expectations, and informal program knowledge. GPA is useful for examining this channel because it responds earlier than completion and may shape subsequent milestones such as qualifying examinations, faculty evaluations, funding renewals, and ultimately the likelihood of completing the degree.

To examine academic performance as a potential mechanism, I re-estimate the field-heterogeneity specification in Equation (2.3) using  $\text{GPA}_{ipt}$  as the dependent variable, where  $\text{GPA}_{ipt}$  denotes the grade outcome of student  $i$  in program  $p$  and entry year  $t$ . I measure GPA using both first-semester GPA and first-year GPA. I then conduct a parallel analysis using the spline specification in Equation (2.4), again replacing the completion outcome with GPA, to assess whether the GPA mechanism is concentrated below the lower international-share knot, where the completion effects are most pronounced.

Table 2.9: Effect of Cohort International Composition on GPA Outcomes: Heterogeneity by Field of Study

| Parameter                               | Variable / Effect                      | First-Semester GPA  | First-Year GPA       |                     |
|-----------------------------------------|----------------------------------------|---------------------|----------------------|---------------------|
| <b>Panel A. Non-STEM programs</b>       |                                        |                     |                      |                     |
| $\beta_1$                               | International student                  | -0.017<br>(0.013)   | -0.039***<br>(0.012) | -0.022*<br>(0.011)  |
| $\beta_2$                               | Cohort international share             | 0.055<br>(0.058)    | 0.002<br>(0.048)     | -0.021<br>(0.028)   |
| $\beta_3$                               | International $\times$ cohort share    | -0.120**<br>(0.057) | -0.164***<br>(0.052) | -0.074<br>(0.046)   |
| $\beta_2 + \beta_3$                     | Total effect on international students | -0.065<br>(0.062)   | -0.162***<br>(0.054) | -0.095**<br>(0.036) |
| $\Delta_1$ SD                           | Effect of +1 SD                        | [-0.012]            | [-0.031]             | [-0.018]            |
| <b>Panel B. STEM programs</b>           |                                        |                     |                      |                     |
| $\beta_1 + \beta_5$                     | International student                  | 0.062***<br>(0.020) | 0.075***<br>(0.018)  | 0.025***<br>(0.008) |
| $\beta_2 + \beta_6$                     | Cohort international share             | -0.054<br>(0.038)   | -0.030<br>(0.039)    | 0.004<br>(0.020)    |
| $\beta_3 + \beta_7$                     | International $\times$ cohort share    | 0.004<br>(0.058)    | -0.012<br>(0.054)    | -0.016<br>(0.023)   |
| $\beta_2 + \beta_3 + \beta_6 + \beta_7$ | Total effect on international students | -0.050<br>(0.050)   | -0.042<br>(0.052)    | -0.012<br>(0.029)   |
| First-semester GPA                      | Included as control                    | No                  | No                   | Yes                 |
| Observations                            |                                        | 11,540              | 11,540               | 11,540              |

*Notes:* The dependent variables are first-semester GPA and first-year GPA. The reported coefficients are linear combinations from a model interacting international student status, cohort international share, and the STEM indicator. Panel A reports effects for non-STEM programs ( $STEM = 0$ ), and Panel B reports effects for STEM programs ( $STEM = 1$ ). The row “Total effect on international students” reports the marginal effect of cohort international share for international students. The effect of a +1 SD increase is calculated by multiplying the group-specific marginal effect by the field-specific standard deviation of cohort international share. The final first-year GPA specification additionally controls for first-semester GPA. All specifications include controls for cohort size, age, age-squared, gender, cohort female share, race/ethnicity indicators, entry-year fixed effects, and program fixed effects. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table 2.9 reports the GPA results by field of study. In non-STEM programs, higher cohort international share is associated with lower GPA among international students. The interaction between international student status and cohort international share is negative and statistically significant for first-semester GPA and for first-year GPA when first-semester GPA is not included as a control. In terms of magnitude, a one-standard-deviation increase in cohort international share is associated with a 0.031-point decline in first-year GPA for international students in non-STEM programs, and the implied decline remains 0.018 points after controlling for first-semester GPA. In STEM programs, by contrast, the corresponding peer-composition effects are small and statistically insignificant across GPA outcomes.

These magnitudes are small relative to the 4.0 GPA scale. Thus, the results should not be interpreted as evidence that grade declines alone explain the lower completion rates. A more cautious interpretation is that increases in international student share generate small but statistically meaningful academic frictions early in training for international students in non-STEM programs. One possible explanation is that non-STEM coursework may rely more on writing, discussion, and familiarity with local academic expectations than STEM coursework. If international students in non-STEM programs have fewer opportunities to interact with domestic peers as the international share rises, they may have less access to this type of informal academic knowledge. By contrast, domestic students are less likely to depend on international peer composition for access to these norms, which may explain why their grades are not similarly affected. These early GPA patterns are consistent with the seven-year completion results, where the negative international peer effects are also concentrated in non-STEM fields.

Table 2.10 reports results from the GPA spline specification using the 35 percent international-share knot. The estimates do not closely mirror the nonlinear pattern found for Ph.D. completion. For domestic students, the marginal effects of cohort international share are statistically insignificant both below and above the knot across all GPA outcomes. For international students, the marginal effect below the knot is positive or close to zero and is not consistently statistically significant. By contrast, the marginal effect above the knot is

Table 2.10: Effect of Cohort International Composition on GPA Outcomes: Nonlinearity by International Share

| Parameter                                               | Variable / Effect                        | First-Semester GPA  | First-Year GPA      |                    |
|---------------------------------------------------------|------------------------------------------|---------------------|---------------------|--------------------|
| Panel A. Estimated coefficients                         |                                          |                     |                     |                    |
| $\beta_1$                                               | International student                    | 0.044***<br>(0.014) | 0.048***<br>(0.014) | 0.014**<br>(0.007) |
| $\beta_2$                                               | Cohort international share               | -0.013<br>(0.036)   | -0.015<br>(0.034)   | -0.002<br>(0.021)  |
| $\beta_3$                                               | Above-knot spline                        | -0.158<br>(0.166)   | -0.153<br>(0.139)   | -0.028<br>(0.080)  |
| $\beta_4$                                               | International $\times$ cohort share      | 0.074<br>(0.048)    | 0.080*<br>(0.042)   | 0.035*<br>(0.020)  |
| $\beta_5$                                               | International $\times$ above-knot spline | -0.277<br>(0.228)   | -0.271<br>(0.213)   | -0.182*<br>(0.108) |
| Panel B. Marginal effects of cohort international share |                                          |                     |                     |                    |
| $\beta_2$                                               | Domestic students, below knot            | -0.013<br>(0.036)   | -0.015<br>(0.034)   | -0.002<br>(0.021)  |
| $\beta_2 + \beta_3$                                     | Domestic students, above knot            | -0.172<br>(0.152)   | -0.168<br>(0.128)   | -0.030<br>(0.070)  |
| $\beta_2 + \beta_4$                                     | International students, below knot       | 0.061<br>(0.044)    | 0.065*<br>(0.039)   | 0.033<br>(0.021)   |
| $\Delta_1$ SD                                           | Effect of +1 SD                          | [0.007]             | [0.008]             | [0.004]            |
| $\beta_2 + \beta_3 + \beta_4 + \beta_5$                 | International students, above knot       | -0.375**<br>(0.165) | -0.360**<br>(0.172) | -0.177*<br>(0.098) |
| $\Delta_1$ SD                                           | Effect of +1 SD                          | [-0.064]            | [-0.061]            | [-0.030]           |
| First-semester GPA                                      | Included as control                      | No                  | No                  | Yes                |
| Observations                                            |                                          | 11,540              | 11,540              | 11,540             |

*Notes:* The dependent variables are first-semester GPA and first-year GPA. Each column reports estimates from a linear spline specification with a 35 percent knot in cohort international share. The above-knot spline is defined as  $(\text{ShareInternational}_{ipt} - 0.35)_+$ . Panel B reports linear combinations corresponding to the marginal effect of cohort international share below and above the knot for domestic and international students. The +1 SD effects are calculated using the standard deviation of cohort international share among cohorts below the 35 percent knot and above the 35 percent knot, 0.12 and 0.17, respectively. The final first-year GPA specification additionally controls for first-semester GPA. All specifications include controls for cohort size, age, age-squared, gender, cohort female share, race/ethnicity indicators, entry-year fixed effects, and program fixed effects. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

negative and statistically significant for first-semester GPA and first-year GPA, including the specification that controls for first-semester GPA.

This pattern suggests that GPA is unlikely to be the main channel explaining the lower

completion rates observed below the lower international-share knot. Instead, the GPA results point to a different form of academic adjustment: among cohorts with relatively high international representation, increases in the international share are associated with lower GPA for international students. When scaled by a one-standard-deviation increase in cohort international share above the knot, the implied effects are declines of 0.064 points in first-semester GPA, 0.061 points in first-year GPA, and 0.030 points in first-year GPA after controlling for first-semester GPA. Although these magnitudes remain modest relative to the 4.0 GPA scale, they are larger than the corresponding GPA changes implied by the field heterogeneity estimates in Table 2.9.

Taken together, the GPA results provide evidence of early academic frictions associated with international peer composition, but they do not fully explain the completion patterns documented in Sections 2.6.1 and 2.6.3. The field-heterogeneity estimates are consistent with the completion results, as negative GPA effects are concentrated among international students in non-STEM programs. However, the spline estimates do not mirror the nonlinear completion pattern: GPA declines are observed only above the 35 percent knot, whereas the adverse completion effects are concentrated below the lower international-share knot. This suggests that grades capture one dimension of the adjustment process during doctoral training, but other margins, such as persistence and dropout timing, may be more important for understanding why international peer composition affects eventual degree completion.

## Dropout Timing

I next examine dropout timing as a potential mechanism through which international peer composition may affect timely Ph.D. completion. This analysis serves two purposes. First, it identifies whether adverse peer effects are associated with earlier exits from the program. Second, if there is no evidence of increased dropout, it helps assess whether lower completion within a fixed time horizon is more likely to reflect delayed graduation rather than attrition. Figure 2.3 plots annual enrollment, dropout, and graduation rates for STEM and non-STEM programs by year since entry. The figure shows that dropout is concentrated in

the early and middle years of doctoral study, especially between the second and third years, while graduation becomes more common after the fifth year and roughly half of all students complete the degree by the end of the sixth year.

To examine dropout timing as a potential mechanism, I re-estimate the field-heterogeneity specification in Equation (2.3) using cumulative dropout indicators as the dependent variables. For each program year  $r \in \{1, \dots, 6\}$ , the outcome equals one if student  $i$  in program  $p$  and entry year  $t$  has dropped out by the end of year  $r$ , and zero otherwise. I then conduct a parallel analysis using the spline specification in Equation (2.4), again replacing the completion outcome with cumulative dropout indicators, to assess whether dropout responses are concentrated below the lower international-share knot, where the completion effects are most pronounced. Because the outcomes are cumulative, Column 1 shows dropout by the end of the first year, Column 2 shows dropout by the end of the second year, and later columns extend this measure through Year 6.

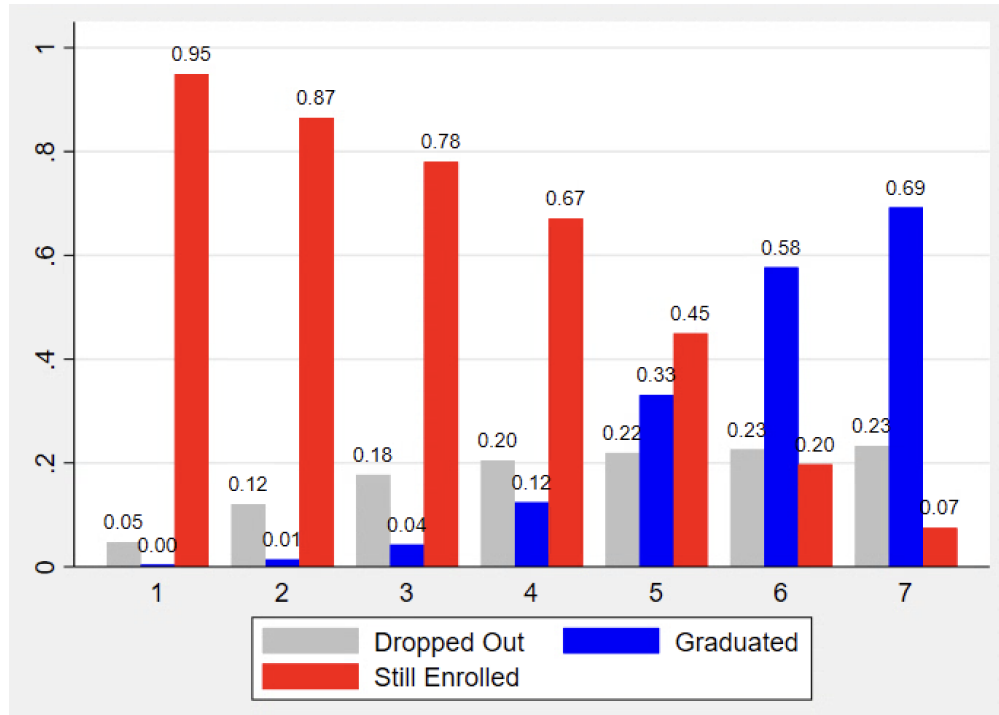
Table 2.11 reports cumulative dropout estimates by field of study. For domestic students, the estimates are essentially flat: cohort international share is small and statistically insignificant in every year in both STEM and non-STEM programs. This is consistent with the earlier completion and GPA results, which show no evidence of international peer effects on domestic students.

The main pattern appears among international students in non-STEM programs. In STEM programs, the total effect of cohort international share is small and statistically insignificant throughout Years 1–6. In non-STEM programs, however, the total effect is positive in every year and becomes statistically significant starting in Year 2. The largest jump occurs between Years 2 and 3, when the estimate rises from 0.118 to 0.249. Because the outcomes are cumulative, this increase suggests that the dropout gap opens mainly around the third year rather than accumulating steadily over time.

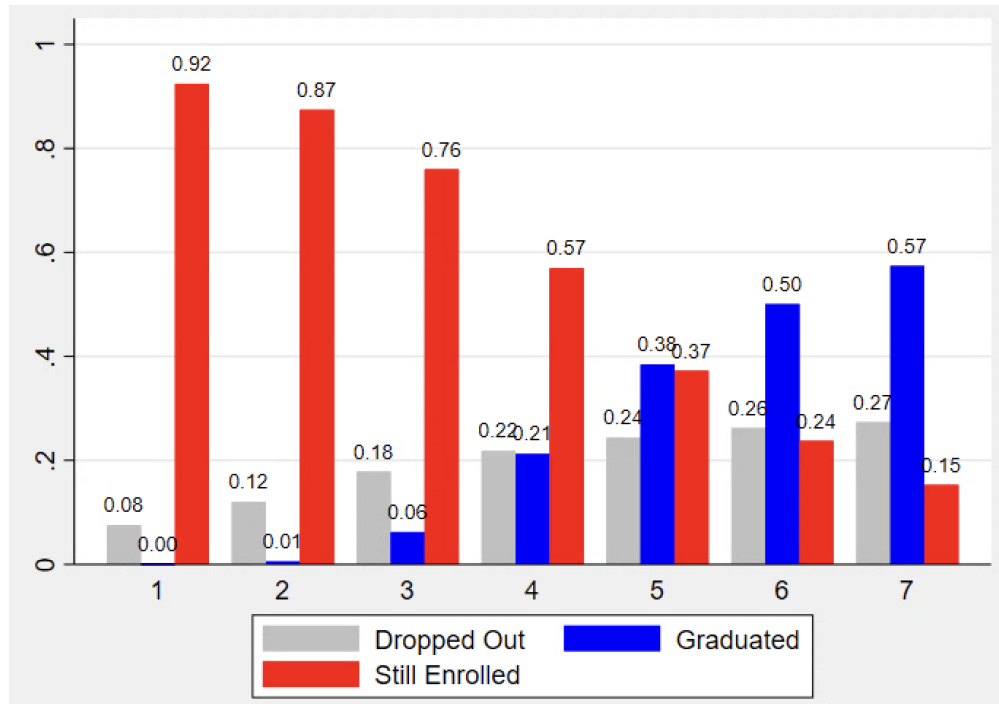
One possible explanation for this timing is a master’s-level exit, in which a student leaves doctoral study after earning an intermediate master’s degree.<sup>19</sup> At The Ohio State

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<sup>19</sup>Related qualitative research describes this pathway as “mastering out” (Maher et al., 2020).



(a) STEM programs



(b) Non-STEM programs

Figure 2.3: Dropout and graduation rates by year of enrollment. The x-axis measures program year. The y-axis indicates the fraction of students in the main estimation sample belonging to each category, dropped out, graduated, or still enrolled, measured at the end of each program year.

Table 2.11: Effect of Cohort International Composition on Ph.D. Dropout by Field

| Parameter                               | Variable / Effect                      | Dropped Out by End of Program Year |                     |                      |                      |                      |                      |
|-----------------------------------------|----------------------------------------|------------------------------------|---------------------|----------------------|----------------------|----------------------|----------------------|
|                                         |                                        | Year 1                             | Year 2              | Year 3               | Year 4               | Year 5               | Year 6               |
| Panel A. Non-STEM programs              |                                        |                                    |                     |                      |                      |                      |                      |
| $\beta_1$                               | International student                  | -0.067***<br>(0.026)               | -0.061**<br>(0.028) | -0.132***<br>(0.028) | -0.116***<br>(0.039) | -0.129***<br>(0.040) | -0.109**<br>(0.044)  |
| $\beta_2$                               | Cohort international share             | -0.015<br>(0.065)                  | 0.027<br>(0.058)    | 0.035<br>(0.061)     | 0.032<br>(0.065)     | 0.006<br>(0.067)     | 0.008<br>(0.065)     |
| $\beta_3$                               | International $\times$ cohort share    | 0.111**<br>(0.046)                 | 0.090<br>(0.058)    | 0.214***<br>(0.062)  | 0.153**<br>(0.067)   | 0.156**<br>(0.067)   | 0.114<br>(0.075)     |
| $\beta_2 + \beta_3$                     | Total effect on international students | 0.096<br>(0.063)                   | 0.118*<br>(0.065)   | 0.249***<br>(0.076)  | 0.185***<br>(0.069)  | 0.162**<br>(0.067)   | 0.122*<br>(0.070)    |
| $\Delta$                                | Change from previous year              | 0.096                              | 0.022               | 0.131                | -0.064               | -0.023               | -0.040               |
| Panel B. STEM programs                  |                                        |                                    |                     |                      |                      |                      |                      |
| $\beta_1 + \beta_5$                     | International student                  | -0.004<br>(0.010)                  | -0.022<br>(0.017)   | -0.044**<br>(0.021)  | -0.065***<br>(0.023) | -0.073***<br>(0.024) | -0.075***<br>(0.023) |
| $\beta_2 + \beta_6$                     | Cohort international share             | 0.002<br>(0.018)                   | 0.018<br>(0.027)    | 0.037<br>(0.037)     | 0.039<br>(0.037)     | 0.042<br>(0.036)     | 0.048<br>(0.038)     |
| $\beta_3 + \beta_7$                     | International $\times$ cohort share    | -0.003<br>(0.023)                  | -0.012<br>(0.038)   | -0.020<br>(0.048)    | -0.000<br>(0.052)    | 0.008<br>(0.051)     | 0.006<br>(0.051)     |
| $\beta_2 + \beta_3 + \beta_6 + \beta_7$ | Total effect on international students | -0.001<br>(0.021)                  | 0.006<br>(0.033)    | 0.017<br>(0.038)     | 0.038<br>(0.042)     | 0.050<br>(0.043)     | 0.054<br>(0.043)     |
| Observations                            |                                        | 11,540                             | 11,540              | 11,540               | 11,540               | 11,540               | 11,540               |

*Notes:* The dependent variables are cumulative dropout indicators measured by the end of each program year. The reported coefficients are linear combinations from a model interacting international student status, cohort international share, and the STEM indicator. Panel A reports effects for non-STEM programs ( $STEM = 0$ ), and Panel B reports effects for STEM programs ( $STEM = 1$ ). The row “Total effect on international students” reports the marginal effect of cohort international share for international students. The  $\Delta$  row reports the change in the Non-STEM total effect relative to the previous program year. All specifications include controls for cohort size, age, age-squared, gender, cohort female share, race/ethnicity indicators, entry-year fixed effects, and program fixed effects. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

University, students in several non-STEM doctoral programs can earn an en route master's degree around the second year.<sup>20</sup> Students who face difficulties early in the program may therefore wait until they satisfy these requirements before leaving, which would concentrate doctoral exits around the third year.

Overall, the dropout results point to a persistence-related mechanism. In non-STEM programs, international students in cohorts with higher international shares are more likely to leave the Ph.D. program. The fact that this effect is most visible around the third year does not necessarily mean that the difficulties begin in the third year. Instead, some students may experience difficulties earlier but remain enrolled until they can leave with an intermediate degree, such as an en route master's degree.

Table 2.12 reports the dropout spline results using the 35 percent international-share knot. Unlike the completion spline results, the dropout estimates do not show a clear or statistically robust pattern of nonlinearity. For domestic students, cohort international share has no consistent relationship with cumulative dropout either below or above the knot. For international students, the below-knot marginal effects are positive in all years, but they are statistically significant at the 10 percent level only in Years 1 and 3 and are otherwise imprecisely estimated. Above the knot, the marginal effects are also statistically insignificant throughout and change sign over time.

Overall, the dropout spline results provide suggestive evidence that the nonlinear completion effects may operate partly through dropout. For international students, the below-knot estimates are positive in most years, whereas the above-knot estimates do not indicate a comparable increase in dropout. This pattern is consistent with the completion results, where adverse international peer effects are concentrated at lower levels of international representation. Because the below-knot dropout estimates are smaller than the completion effects and are not consistently statistically significant, the evidence should be interpreted as suggestive rather than conclusive. Still, the alignment between the completion and dropout patterns points to persistence and attrition as an important potential mechanism.

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<sup>20</sup>Doctoral students typically earn an en route master's during the second year in [history](#) and [English](#); in [sociology](#), master's-level requirements are normally completed by the beginning of the third year.

Table 2.12: Effect of Cohort International Composition on Ph.D. Dropout: Nonlinearity by International Share

| Parameter                                               | Variable / Effect                        | Dropped Out by End of Program Year |                      |                      |                      |                      |                      |
|---------------------------------------------------------|------------------------------------------|------------------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
|                                                         |                                          | Year 1                             | Year 2               | Year 3               | Year 4               | Year 5               | Year 6               |
| Panel A. Estimated coefficients                         |                                          |                                    |                      |                      |                      |                      |                      |
| $\beta_1$                                               | International student                    | -0.012*<br>(0.007)                 | -0.028***<br>(0.010) | -0.050***<br>(0.012) | -0.064***<br>(0.013) | -0.071***<br>(0.014) | -0.070***<br>(0.014) |
| $\beta_2$                                               | Cohort international share               | 0.019<br>(0.030)                   | 0.047<br>(0.032)     | 0.050<br>(0.038)     | 0.062<br>(0.040)     | 0.047<br>(0.039)     | 0.033<br>(0.039)     |
| $\beta_3$                                               | Above-knot spline                        | -0.202*<br>(0.105)                 | -0.235<br>(0.170)    | -0.098<br>(0.197)    | -0.195<br>(0.211)    | -0.114<br>(0.202)    | 0.065<br>(0.204)     |
| $\beta_4$                                               | International $\times$ cohort share      | 0.022<br>(0.029)                   | -0.011<br>(0.035)    | 0.014<br>(0.040)     | -0.001<br>(0.045)    | 0.012<br>(0.046)     | 0.010<br>(0.048)     |
| $\beta_5$                                               | International $\times$ above-knot spline | 0.060<br>(0.127)                   | 0.138<br>(0.209)     | -0.030<br>(0.258)    | 0.125<br>(0.277)     | 0.097<br>(0.266)     | -0.004<br>(0.253)    |
| Panel B. Marginal effects of cohort international share |                                          |                                    |                      |                      |                      |                      |                      |
| $\beta_2$                                               | Domestic students, below knot            | 0.019<br>(0.030)                   | 0.047<br>(0.032)     | 0.050<br>(0.038)     | 0.062<br>(0.040)     | 0.047<br>(0.039)     | 0.033<br>(0.039)     |
| $\beta_2 + \beta_3$                                     | Domestic students, above knot            | -0.183**<br>(0.086)                | -0.188<br>(0.154)    | -0.048<br>(0.182)    | -0.133<br>(0.191)    | -0.066<br>(0.183)    | 0.097<br>(0.187)     |
| $\beta_2 + \beta_4$                                     | International students, below knot       | 0.042*<br>(0.025)                  | 0.036<br>(0.034)     | 0.064*<br>(0.037)    | 0.061<br>(0.038)     | 0.060<br>(0.038)     | 0.043<br>(0.040)     |
| $\beta_2 + \beta_3 + \beta_4 + \beta_5$                 | International students, above knot       | -0.101<br>(0.071)                  | -0.060<br>(0.097)    | -0.064<br>(0.123)    | -0.010<br>(0.149)    | 0.043<br>(0.152)     | 0.104<br>(0.148)     |
| Observations                                            |                                          | 11,540                             | 11,540               | 11,540               | 11,540               | 11,540               | 11,540               |

*Notes:* The dependent variables are cumulative dropout indicators measured by the end of each program year. Each column reports estimates from a linear spline specification with a 35 percent knot in cohort international share. The above-knot spline is defined as  $(\text{ShareInternational}_{ipt} - 0.35)_+$ . Panel B reports linear combinations corresponding to the marginal effect of cohort international share below and above the knot for domestic and international students. The +1 SD effects are calculated using the standard deviation of cohort international share among cohorts below the 35 percent knot and above the 35 percent knot, 0.12 and 0.17, respectively. All specifications include controls for cohort size, age, age-squared, gender, cohort female share, race/ethnicity indicators, entry-year fixed effects, and program fixed effects. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

## 2.7 Discussion and Conclusion

This paper examines how the international composition of doctoral cohorts affects students' academic progress. Using transcript-level administrative records from Ohio public universities between 2005 and 2020, I exploit year-to-year variation in international student shares within the same doctoral program to estimate peer effects on Ph.D. completion, GPA, and dropout timing.

The main results show no evidence that higher international peer exposure affects doctoral outcomes on average. Domestic students are not adversely affected by the share of international students in their entering cohort, either in completion, GPA, or dropout outcomes.

This finding is consistent with prior research showing limited evidence that international students crowd out or harm domestic students' graduate education outcomes (Borjas, 2007; Regets, 2007; Shih, 2017). The aggregate effect for international students is also statistically indistinguishable from zero. However, the aggregate null effect masks important heterogeneity. Negative peer effects are concentrated among international students in non-STEM programs and in cohorts where international students make up a relatively small share of the entering class. By contrast, the estimates are close to zero in STEM programs and in cohorts where international students constitute a more substantial presence within the cohort.

The mechanism analyses provide more nuance to the main findings. The analyses of GPA outcomes show evidence of early academic frictions among international students in non-STEM programs, but the magnitudes are small and do not fully explain the completion patterns. Dropout timing provides clearer evidence of a persistence-related mechanism in non-STEM programs: international students in cohorts with higher international shares are more likely to leave the Ph.D. program, with the increase in dropout concentrated around the period when students may complete an intermediate master's degree. This timing suggests that some students who encounter difficulties earlier may remain enrolled until they can leave with an en route master's degree. The spline analyses further indicate that this attrition channel is most relevant when international students remain a relatively small presence in the cohort. Together, these patterns suggest that persistence, rather than grades alone, is the more important mechanism linking international peer composition to doctoral completion.

Taken together, the findings suggest that the effects of an increase in international peers depend less on the increase itself than on the structure of doctoral training environments. A higher international student share does not appear to harm domestic students or reduce completion on average. Instead, negative effects arise in non-STEM fields, where students are less often embedded in structured laboratory teams or research groups, and among cohorts in which international students remain a relatively small presence. This nonlinear pattern is consistent with the idea that international peer effects may change once international students become numerous enough to provide stronger peer support, information sharing,

and social belonging within the cohort.

These results point to the value of support-oriented responses. Rather than suggesting that international enrollment itself is the central problem, the findings indicate that doctoral outcomes may depend on how students are integrated into their programs. Programs may therefore improve persistence by strengthening advising transparency, peer integration, and mentoring during the early stages of doctoral training. Several limitations remain. The data do not directly observe advising quality, funding stability, research-group assignment, or informal peer networks, all of which may shape how international peer composition affects doctoral progress. The analysis is also based on public universities in one state, so the findings may differ in other institutional settings. Nevertheless, the evidence shows that international peer effects in doctoral education are not uniform: they depend on who is affected, where students are trained, and whether international representation has reached a level that changes the peer environment.

## Chapter 3

# Diversity in Ph.D. Programs: Gender, Race, and Language

### 3.1 Introduction

Over the past several decades, the composition of U.S. doctoral programs has changed substantially. This shift reflects two broad forces: efforts to broaden the representation of women and underrepresented racial and ethnic groups in higher education ([Orlans, 1992](#); [Bleemer, 2022](#)) and the rising share of international students in graduate training ([Bound et al., 2021](#); [National Center for Science and Engineering Statistics, 2025a](#)). Together, these changes have made entering cohorts more heterogeneous in gender, race/ethnicity, and language. This growing heterogeneity may expand the knowledge, experiences, and networks available to students, while also raising the costs of communication and coordination among peers ([Lazear, 1999](#); [Alesina and Ferrara, 2005](#)). Yet existing evidence on diversity in higher education comes largely from undergraduate settings ([Dasgupta et al., 2015](#); [Dills, 2018](#); [Luo, 2025](#); [Anelli et al., 2023](#)). This leaves an important gap: doctoral training is organized around program-specific milestones, including coursework, examinations, candidacy, and dissertation research, and students' progress is shaped by relationships with peers and

faculty ([Gardner, 2007](#)). Findings from undergraduate settings may therefore not directly generalize to doctoral education.

This paper studies whether year-to-year changes in doctoral cohort composition along gender, race/ethnicity, and language dimensions affect students' academic progress, and whether these effects vary by student characteristics. I use student-level administrative records from the Ohio Longitudinal Data Archive for doctoral students at all public universities in Ohio from Fall 2009 through Spring 2020. By linking enrollment histories, demographics, academic performance, program information, and degree records, the data allow me to define entering cohorts within doctoral programs and assign each student the peer environment at entry. I examine outcomes that capture academic progress over short-, medium-, and long-run horizons, including first-year GPA, persistence, attrition, and Ph.D. completion within seven years. The empirical strategy compares students entering the same doctoral program in different years, exploiting plausibly idiosyncratic within-program year-to-year fluctuations in cohort composition.<sup>1</sup>

I document three main findings. First, some dimensions of cohort diversity are associated with lower timely Ph.D. completion. A one-standard-deviation increase in within-cohort linguistic distance lowers the probability of completing the Ph.D. within seven years by about 4 percentage points, with negative effects for both domestic and international students. Racial/ethnic diversity is also associated with lower seven-year completion, with larger and statistically significant estimates for non-White students. In contrast, gender balance has no detectable association with seven-year Ph.D. completion.

Second, the effects are nonlinear and vary sharply across fields. The negative effect of racial/ethnic diversity is concentrated in cohorts with relatively low baseline race/ethnicity diversity, while the effect of linguistic distance emerges primarily in cohorts that are already linguistically diverse. These nonlinearities suggest that the marginal effect of diversity depends on the baseline peer environment. Additional race/ethnicity heterogeneity appears most costly when baseline representation is low, consistent with minority students

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<sup>1</sup>I support the identifying variation using balance tests for observable cohort characteristics and Monte Carlo simulations.

facing greater integration frictions in otherwise homogeneous cohorts. Additional linguistic distance, by contrast, appears most costly when cohorts are already linguistically diverse, consistent with communication frictions becoming more binding once language differences are salient. Heterogeneity in effects across fields is also substantial. Race/ethnicity diversity reduces completion only in non-STEM programs, whereas linguistic distance reduces completion only in STEM programs. These patterns indicate that the effects of diversity depend both on the dimension of diversity and on the academic environment in which peer interaction occurs.

Third, I examine mechanisms by testing whether the completion effects operate through attrition or through graded coursework performance. The evidence suggests language-related frictions during key transitions in doctoral training. Linguistic distance increases dropout primarily in the first and third years, corresponding to entry into a new academic environment and the transition from coursework to research. By contrast, racial/ethnic diversity does not significantly increase dropout, suggesting that its effect on seven-year completion may reflect slower progress rather than exit from the program. GPA results provide little evidence that cohort composition affects graded performance: gender balance, racial/ethnic diversity, and linguistic distance are not systematically associated with first-term, first-year, or final cumulative GPA. These patterns suggest that cohort composition affects doctoral progress mainly through persistence and integration rather than through coursework performance.

Overall, the findings indicate that diversity in doctoral cohorts has heterogeneous and context-dependent effects. Diversity does not operate as a single, uniform treatment: gender balance, race/ethnicity diversity, and linguistic distance capture different features of the cohort environment and have different associations with student progress. Language-related heterogeneity is the most robust source of completion penalties, and the timing of dropout effects suggests that these penalties operate through communication and integration frictions rather than through contemporaneous course performance.

This paper makes three main contributions. First, it provides the first evidence, to my

knowledge, on the role of language distance in doctoral cohort peer effects, contributing to the literature on graduate peer effects in a setting where international students play an increasingly central role in doctoral training. Second, it moves beyond representation-based measures of peer composition by measuring gender balance, racial/ethnic diversity, and linguistic distance. This approach examines the structure of cohort heterogeneity rather than simply the share of any particular group, revealing persistence barriers that would be missed by standard peer-share measures such as the share of female, non-White, or international students. Third, the paper provides potential mechanism evidence on when and how cohort diversity matters for doctoral progress. The evidence shows that the main effects operate through persistence and integration rather than graded coursework performance, with language-related dropout effects concentrated during early adjustment and the transition from coursework to research.

The remainder of this chapter is organized as follows. Section 3.2 reviews the related literature and motivates the empirical focus on gender balance, racial/ethnic diversity, and linguistic distance. Section 3.3 describes the data and construction of the cohort-composition measures. Section 3.4 outlines the empirical strategy and identifying variation. Section 3.5 presents the main results, including heterogeneity analyses, nonlinearities, and evidence on dropout timing and GPA. Section 3.6 examines mechanism evidence. Section 3.7 reports additional analyses and robustness checks, and Section 3.8 concludes.

## 3.2 Peer Diversity in Higher Education

Previous research has shown that peer composition can influence achievement, behavior, and educational choices, and that these effects vary across settings and peer groups (e.g., [Epple and Romano, 2011](#); [Sacerdote, 2011](#)). In higher education settings, related evidence shows that peer diversity and peer composition can affect college experiences, academic outcomes, and field choice (e.g., [Bowman, 2010](#); [Zölitz and Feld, 2021](#)). Yet much of this evidence examines one dimension of diversity at a time, such as gender, race/ethnicity,

or language background, leaving limited evidence on multidimensional peer composition. Moreover, much of the empirical evidence is concentrated in undergraduate settings, leaving much less known about peer diversity in graduate education. I organize the discussion around three dimensions of peer diversity—gender, race/ethnicity, and language background—before turning to the smaller literature on graduate peer environments.

The largest body of related evidence examines gender composition, but this literature points to several distinct channels rather than a single uniform effect. In undergraduate settings, the evidence is mixed on achievement but stronger on educational choices in gender-typed fields. [Oosterbeek and van Ewijk \(2014\)](#), using random assignment to tutorial groups, find limited average effects of peer gender composition on university performance. By contrast, studies of field choice show that gender composition can shape students’ subsequent specialization decisions. For example, [Zölitz and Feld \(2021\)](#) show that peer gender affects major choice in business school, while evidence from engineering indicates that same-gender peer mentors can improve women’s belonging, well-being, internships, and STEM persistence ([Wu et al., 2022](#)). Related work further suggests that these effects depend on institutional context, grading incentives, and the margin of choice being studied ([Griffith and Main, 2019](#); [Fairlie et al., 2020](#); [Calkins et al., 2023](#); [Butcher et al., 2024](#)). Relative to this literature, this paper offers a different perspective on peer composition by moving from measures based on the share of a particular group toward measures of balance in the overall composition of entering Ph.D. cohorts. In doing so, it treats peer environments as cohort-level structures rather than as simple exposure to one group or another, and examines how those structures relate to persistence and degree completion in doctoral education.

A second strand of the literature on peer effects examines racial/ethnic diversity. This literature emphasizes that racially and ethnically diverse peer environments may broaden perspectives, increase cross-racial/ethnic interactions, and foster civic and democratic engagement. Using undergraduate student survey evidence, [Gurin et al. \(2002\)](#) show that interactions with racially and ethnically diverse peers are associated with greater active thinking, intellectual engagement, perspective taking, and democratic participation. In an

experimental undergraduate setting, [Antonio et al. \(2004\)](#) show that racial/ethnic and opinion diversity in discussion groups increases both the novelty of contributions and students' integrative complexity. More recent studies examine academic outcomes directly. [Dills \(2018\)](#) documents heterogeneous racial/ethnic peer effects in required first-semester college courses: White students earn higher grades in classes with more students of color, whereas lower-SAT students of color earn lower grades when exposed to more non-White classmates. [Lau \(2022\)](#) exploits quasi-random assignment to first-year writing sections and finds that greater racial/ethnic classroom diversity increases graduation GPA, improves first-year grades for women, and affects major choice among White students. Relative to these studies, this paper shifts the focus from undergraduate classrooms to entering Ph.D. cohorts and examines persistence and degree completion rather than field choice or starting salaries.

A third, more limited strand of the literature examines how language-related diversity shapes students' experiences and academic outcomes in higher education. Because data on students' native languages and direct measures of linguistic diversity are limited, papers in this literature typically rely on foreign-student status or English proficiency as their main measures. [Chevalier et al. \(2020\)](#) exploit quasi-random assignment to undergraduate seminar groups and find that linguistic diversity among non-native speakers improves their performance, particularly among lower-achieving students, without harming native speakers. By contrast, [Anelli et al. \(2023\)](#) show that, in introductory undergraduate math courses, exposure to foreign classmates reduces domestic students' likelihood of obtaining STEM degrees and entering STEM occupations, with effects concentrated in classes where foreign classmates have weaker English proficiency. These contrasting findings suggest that the implications of language-related diversity may depend on how linguistic exposure is defined and measured. I therefore use the country-of-origin information available in the OLDA data to link students to their likely native languages and construct an index of linguistic distance among those languages, allowing for a more detailed analysis of language-based communication frictions and their implications for persistence and Ph.D. completion.

A smaller but growing literature examines peer composition and diversity in graduate

education, where peer environments may operate differently than in undergraduate settings. Graduate students are often organized into small program-entry cohorts and interact repeatedly through coursework, research groups, advising networks, and funding structures. In STEM doctoral programs, [Bostwick and Weinberg \(2022\)](#) show that the gender composition of entering cohorts affects women’s persistence and degree completion, highlighting the importance of same-cohort peers in graduate training. Related work on international students finds that international enrollment can reshape graduate program resources and domestic enrollment through cross-subsidization mechanisms ([Shih, 2017](#)). Studies of doctoral education further emphasize that persistence is shaped by departmental climate, advising, and sociocultural support, particularly for students from historically underrepresented groups (e.g., [Posselt, 2018](#)). More recently, [Mitra et al. \(2026\)](#) provide evidence on broader cohort diversity, showing that greater racial/ethnic diversity in MBA and law-school cohorts is associated with higher starting salaries at graduation. Taken together, these studies suggest that graduate peer environments are consequential. However, existing evidence remains concentrated on specific dimensions of composition, and particular program types.

Taken together, this literature shows that peer composition can shape students’ academic trajectories, but it also leaves three important gaps. First, most studies examine a single dimension of diversity rather than the multidimensional structure of peer environments. Second, the evidence is concentrated in undergraduate classrooms, where peer interactions may differ substantially from the repeated and program-based interactions that characterize doctoral training. Third, relatively little is known about how cohort-level diversity relates to persistence and degree completion, two central margins of doctoral success. This paper addresses these gaps by studying entering Ph.D. cohorts and measuring gender balance, racial/ethnic diversity, and language distance, thereby shifting the focus from exposure to a particular group toward peer diversity in doctoral education.

### 3.2.1 Conceptual Framework

Cohort diversity may matter differently in doctoral programs than in undergraduate settings because doctoral students move through small cohorts and depend heavily on informal peer exchange. I conceptualize it as a change in what information, perspectives, and support are available within a cohort, and who can access them.

Diversity can improve peer exchange by expanding the range of knowledge, experiences, and support within a cohort. International and domestic students may exchange information about global research communities, local institutional norms, funding, advising, and career pathways, while women and racially minoritized students may gain same-group support, belonging, and strategic information. These mechanisms are consistent with evidence that diverse interactions promote perspective taking and intellectual engagement ([Gurin et al., 2002](#)), and that diverse discussion groups produce more novel and integratively complex contributions ([Antonio et al., 2004](#)).

At the same time, diversity does not automatically become useful exchange. International students may face language barriers that limit participation in academic and social interaction ([Kuo, 2011](#)). In male-dominated or predominantly White programs, women and racially minoritized students may experience heightened pressure to prove their competence or belonging when they are one of few members of their group ([Clance and Imes, 1978](#); [Thompson and Sekaquaptewa, 2002](#)). Thus, cohort diversity can increase the potential value of peer exchange while also creating uneven costs across groups.

This framework implies that cohort diversity may have heterogeneous and nonlinear effects. Its consequences should depend on the type and level of diversity, students' positions within the cohort, and whether diverse cohorts become integrated peer networks. Guided by this framework, I examine whether the effects of cohort diversity vary across student groups and diversity levels, and which students benefit from or bear the costs of more diverse cohorts.

### 3.3 Data

This study uses student-level administrative records from the Ohio Longitudinal Data Archive (OLDA)<sup>2</sup>, which links enrollment, demographic, academic, program, and degree-completion records for students in all Ohio public universities. These data allow me to construct entering cohorts within narrowly defined doctoral programs and to link each student to the composition of the peer environment they faced when beginning doctoral study.

The data include doctoral enrollment and degree records from Fall 2009 through Spring 2020. I use these records to identify research doctoral students<sup>3</sup> at first enrollment and to follow their academic progress, persistence, and degree attainment over time. For the main analysis, I restrict the entering-cohort sample to students who begin their doctoral program no later than Fall 2013. This restriction ensures that every cohort can be observed for a common seven-year completion window and avoids mechanically lower completion rates for later cohorts with shorter observation periods.

The unit of peer exposure is the entering cohort within a program. I define doctoral programs using the six-digit Classification of Instructional Programs (CIP) codes available in OLDA.<sup>4</sup> Programs are defined at the six-digit-CIP-by-institution level, so programs with the same CIP code at different universities are treated as distinct programs. A student's entering cohort is determined by the first term of enrollment in that program.<sup>5</sup> Students who begin in the summer are assigned to the following fall cohort. This definition captures

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<sup>2</sup>The Ohio Longitudinal Data Archive is a project of the Ohio Education Research Center ([oerc.osu.edu](http://oerc.osu.edu)) and provides researchers with centralized access to administrative data. The OLDA is managed by The Ohio State University's CHRR ([chrr.osu.edu](http://chrr.osu.edu)) in collaboration with Ohio's state workforce and education agencies ([olda.ohio.gov](http://olda.ohio.gov)), with those agencies providing oversight and funding. Learn more about our sponsors in the OLDA Acknowledgment section.

<sup>3</sup>Following the OLDA degree classification based on Ohio's Higher Education Information (HEI) Degree/Certificate Earned (DC) file, I restrict the analytic sample to Doctor's Degree–Research/Scholarship programs. I exclude Doctor's Degree–Professional Practice programs, as well as programs classified as Doctor's Degree–Other. See the Ohio Department of Higher Education's HEI DC file documentation: <https://higher.ed.ohio.gov/wps/portal/gov/odhe/data-reports/hei-system/hei-file-doc/hei-enrollment/hei-dc>.

<sup>4</sup>The CIP is a standardized taxonomy of instructional programs developed by the U.S. Department of Education's National Center for Education Statistics. See <https://nces.ed.gov/ipeds/cipcode/>.

<sup>5</sup>The administrative data distinguish four academic terms within each year: spring, summer, fall, and winter.

students who enter the same doctoral field at the same institution at approximately the same time and therefore face a common initial peer environment.

I apply several additional sample restrictions. I first restrict the sample to graduate students enrolled at the main campus of each institution and then retain only doctoral-level programs. I exclude observations with unresolved or missing information on gender, country of origin or race/ethnicity. I also exclude programs with an average entering cohort size below eight students. This restriction is based on each program’s average cohort size over all observed cohorts, rather than any single-year realization, so that sample inclusion is not driven by transitory fluctuations in enrollment. The restriction reduces noise in cohort-level composition measures that are mechanically unstable in very small programs.<sup>6</sup>

### 3.3.1 Outcome Measures

I examine outcomes along three margins of doctoral progress: academic performance, attrition, and degree completion. These outcomes capture different stages of doctoral training and different ways in which cohort composition may matter. Cohort composition may affect students immediately through coursework performance, or more gradually through peer learning, academic integration, collaboration, and decisions to remain enrolled.

The primary outcome is timely Ph.D. completion. I define *Ph.D. completion within seven years* as an indicator equal to one if a student earns the Ph.D. within seven years of initial enrollment in the doctoral program, and zero otherwise. In the estimation sample, 68 percent of students complete the Ph.D. within seven years, 22 percent leave the program before year 7 without completing the degree, and 9 percent remain enrolled beyond the seven-year window. I use a seven-year window because it is long enough to capture standard doctoral completion trajectories while still distinguishing timely completion from substantially delayed degree attainment. This window also provides a consistent observation period across entering cohorts in the administrative records.

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<sup>6</sup>Table 3.19 shows results with alternative minimum cohort-size cutoffs.

I also examine the timing of attrition before completion. I construct a sequence of cumulative dropout indicators for years 1 through 6.<sup>7</sup> For each year  $y \in \{1, \dots, 6\}$ , the indicator equals one if a student exits the doctoral program without completing the Ph.D. by the end of year  $y$ , and zero otherwise. These year-specific outcomes make it possible to assess when cohort composition is associated with attrition. The timing of dropout is informative because exits at different stages of doctoral training may point to different mechanisms. Early dropout may reflect difficulties with initial academic adjustment or social integration, whereas later dropout may be more closely related to research progress, collaboration, advising relationships, or the transition from coursework to independent research.

Finally, I use GPA-based outcomes to measure academic performance during the graded portion of doctoral training. *First-term GPA* measures performance in the student's first enrolled term, while *first-year GPA* measures cumulative performance over the first academic year. These outcomes capture early adjustment to doctoral coursework. I also examine *final GPA*, which measures cumulative GPA at the time of Ph.D. completion, program exit, or last observed enrollment. Because most graded coursework is typically completed during the first two to three years of doctoral study, GPA outcomes provide a measure of course performance rather than the full range of doctoral progress. Comparing GPA outcomes with dropout and completion outcomes helps distinguish academic performance effects from channels operating through continued enrollment, collaboration, information sharing, and integration into the program.

The final estimation sample contains 4,436 doctoral students in 158 entering cohorts across 56 doctoral programs at 10 public universities.<sup>8</sup> Table 3.1 reports summary statistics for the estimation sample. Sixty-eight percent of students complete the Ph.D. within seven years, 9 percent remain enrolled after seven years, and 22 percent drop out before year 7. The average time to degree among completers is 5.30 years, while students spend an average

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<sup>7</sup>Year-specific dropout is measured relative to the student's first Ph.D. enrollment term. Year-1 dropout indicates that the student leaves before reaching year 2.

<sup>8</sup>Bowling Green State University–Main Campus, Cleveland State University, Kent State University at Kent, Miami University–Oxford, Ohio State University–Main Campus, Ohio University–Main Campus, University of Akron Main Campus, University of Cincinnati–Main Campus, University of Toledo, and Wright State University–Main Campus.

of 4.64 years enrolled in the Ph.D. program. The sample is 44 percent female, 39 percent international, and 66 percent enrolled in STEM fields. Students enter at an average age of 27, and average GPAs are high throughout the program, ranging from 3.71 in the first term to 3.86 at completion, exit, or last observed enrollment.

Table 3.1: Summary Statistics

| Variable                       | Full sample ( $N = 4,436$ ) |           |
|--------------------------------|-----------------------------|-----------|
|                                | Mean                        | Std. Dev. |
| Completed Ph.D. within 7 years | 0.68                        | 0.47      |
| Still enrolled at year 7       | 0.09                        | 0.28      |
| Dropped out before year 7      | 0.22                        | 0.42      |
| Years to Ph.D. <sup>a</sup>    | 5.30                        | 1.50      |
| Years enrolled in Ph.D.        | 4.64                        | 1.97      |
| Age at entry                   | 27.05                       | 6.27      |
| Female                         | 0.44                        | 0.50      |
| STEM                           | 0.66                        | 0.47      |
| International                  | 0.39                        | 0.49      |
| First-term GPA                 | 3.71                        | 0.38      |
| First-year GPA                 | 3.72                        | 0.32      |
| Final GPA                      | 3.86                        | 0.23      |

*Notes:* Means for indicator variables can be interpreted as proportions. GPA variables are measured on a 4.0 scale.

<sup>a</sup> Observed only for students who completed a Ph.D., yielding a sample of 3,325 students.

### 3.3.2 Measuring Cohort Composition

I characterize diversity within each entering cohort along three dimensions: gender balance, race/ethnicity diversity, and linguistic distance. These measures are not intended to capture minority representation alone. Rather, they describe the extent to which students from different backgrounds are distributed within each cohort.

**Gender Balance.** I measure gender balance using the distance from gender parity. Let  $f_{pt}$  denote the female share of entering cohort  $t$  in program  $p$ . I define

$$G_{pt} = 1 - 2 |f_{pt} - 0.5|.$$

This index equals one for a cohort that is evenly split between women and men and declines as the gender composition moves away from parity.<sup>9</sup> It reaches zero when all students are of the same gender. Higher values indicate more balanced gender representation.

**Race/Ethnicity Diversity.** I measure race/ethnicity diversity using a Blau (1977) fractionalization index,

$$R_{pt} = 1 - \sum_k s_{kpt}^2,$$

where  $s_{kpt}$  is the share of students in cohort  $t$  and program  $p$  who belong to race/ethnicity category  $k$ . The index can be interpreted as the probability that two randomly selected students from the same cohort belong to different race/ethnicity categories. Figure 3.1 summarizes the race/ethnicity composition of doctoral students in the estimation sample. Students who identify with multiple races are coded as a separate category. American Indian, Alaska Native, Native Hawaiian, and Pacific Islander students are combined into an “Other” category because of small cell sizes. Observations with unresolved race/ethnicity information are excluded from the estimation sample. When race/ethnicity is missing, I use the country-of-origin variable to impute category membership where possible.<sup>10</sup>

White students make up the majority of the sample, while Asian students are the second-largest group. The figure also shows that the East Asian and South Asian categories are largely composed of international students, whereas the White, Black, Hispanic, and multiracial categories are primarily domestic students. This pattern suggests that race/ethnicity diversity in the sample is closely related to the international composition of doctoral cohorts.

Figure 3.2 further separates the same composition by STEM and non-STEM programs. This split shows whether the race/ethnicity composition and international enrollment of doctoral students differ across academic fields, which is important given the strong concentration of international students in STEM programs. The contrast across fields is substantial. While White students make up the clear majority in non-STEM programs, STEM programs are

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<sup>9</sup>The factor of 2 rescales the maximum possible deviation from parity, 0.5, to 1, so that the index equals 1 under perfect balance and 0 when all students are of the same gender.

<sup>10</sup>Appendix Table C3 reports the mapping used to impute race/ethnicity from country of origin.

characterized by a much larger international presence, with international students accounting for a share nearly comparable to that of White students. Thus, aggregate race/ethnicity composition patterns conceal considerable field-level heterogeneity. At the same time, non-STEM programs have nearly twice the share of Black, Hispanic, and multiracial students as STEM programs, indicating that domestic race/ethnicity diversity is also unevenly distributed across fields.

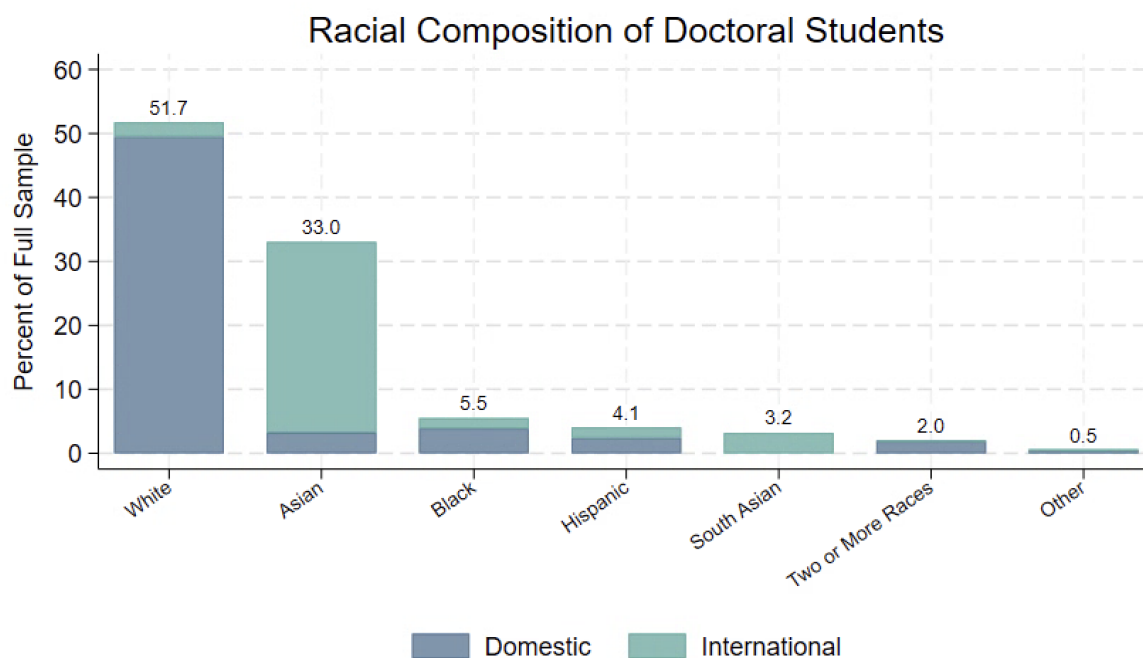


Figure 3.1: Race/Ethnicity Composition of Doctoral Students by International Status

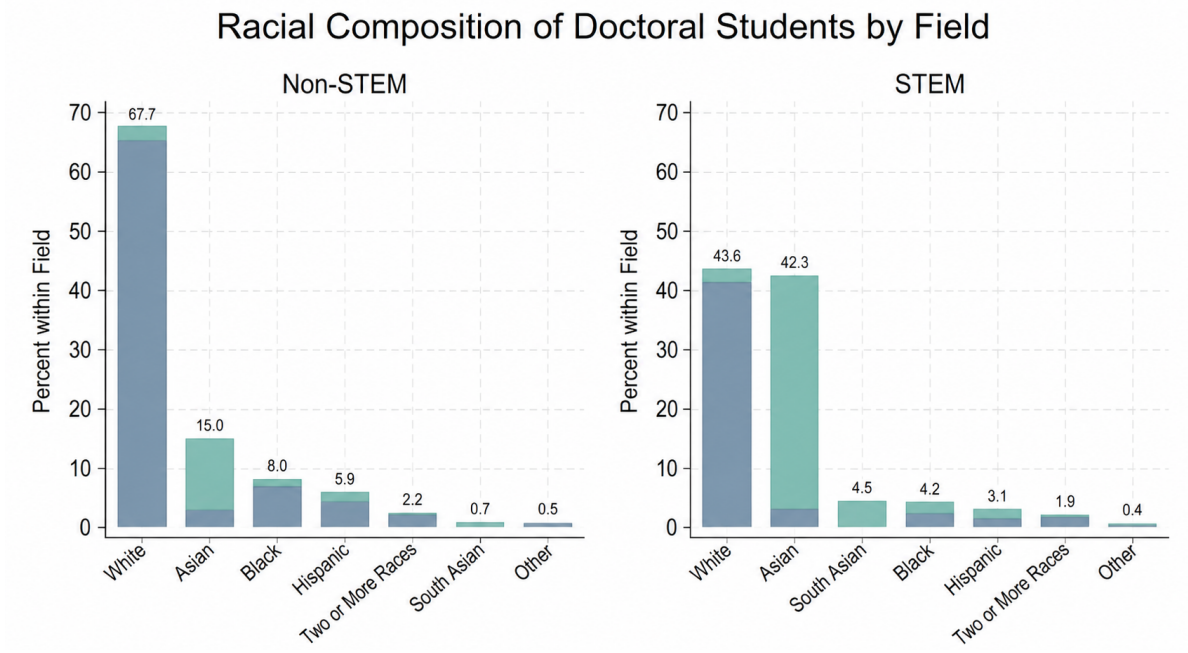


Figure 3.2: Race/Ethnicity Composition of Doctoral Students by International Status and Field

**Linguistic Distance.** I measure linguistic distance using country-pair common-language similarity scores from the *Domestic and International Common Language Database* (DICL) (Gurevich et al., 2024). Because the data do not directly observe students’ spoken languages, I assign language similarity based on students’ countries of origin and merge the DICL country-pair measures into the cohort data.

Let  $CSL_{cc'}$  denote the common-language similarity score between countries  $c$  and  $c'$ , and let  $n_{cpt}$  be the number of students from country  $c$  in entering cohort  $t$  and program  $p$ . I first compute cohort-level linguistic similarity as

$$S_{pt} = \frac{\sum_c \sum_{c'} w_{cc'pt} CSL_{cc'}}{\sum_c \sum_{c'} w_{cc'pt}},$$

where

$$w_{cc'pt} = \begin{cases} n_{cpt}n_{c'pt}, & c \neq c', \\ n_{cpt}(n_{cpt} - 1), & c = c'. \end{cases}$$

The same-country weight excludes self-pairs. I then define linguistic distance as

$$L_{pt} = 1 - S_{pt}.$$

Higher values indicate lower average language similarity among cohort members and therefore greater potential communication costs in peer learning, collaboration, and informal information exchange.

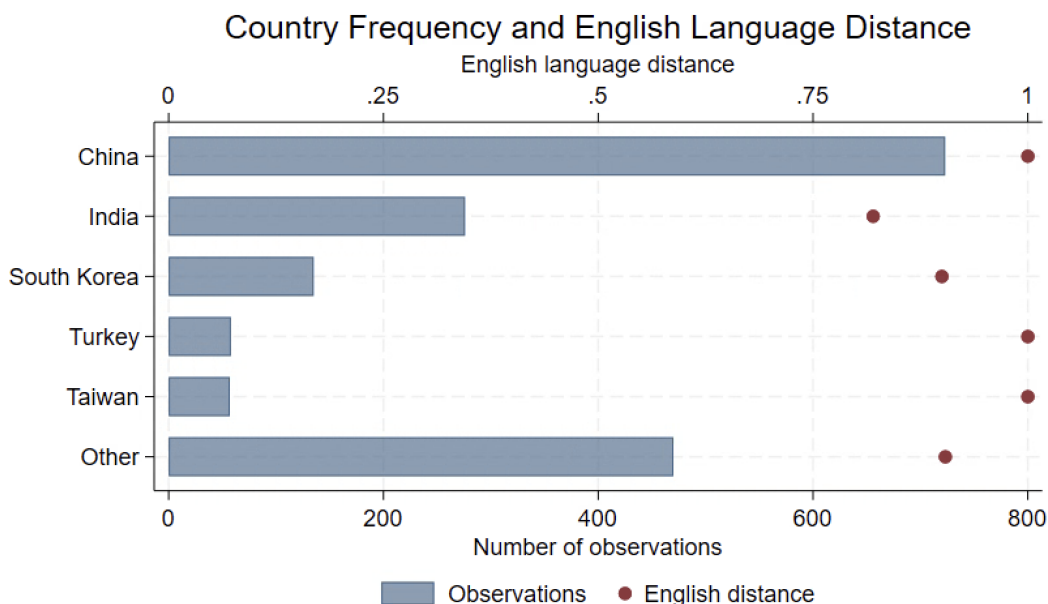


Figure 3.3: Country-of-Origin Frequency and English-Language Distance

Figure 3.3 shows the distribution of students’ countries of origin among international students, alongside each country’s English-language distance measure. China accounts for the largest share of observations, followed by India and South Korea. The red markers indicate the English-language distance assigned to each country, with higher values representing greater linguistic distance from English. The “Other” category combines all remaining countries outside the top five and is assigned the count-weighted average English-language distance among those countries.

Table 3.2 reports summary statistics for these cohort composition measures. The unit of observation is the student, so the table describes the distribution of cohort environments

faced by students in the estimation sample. The measures display substantial variation: the gender balance index has a mean of 0.61, race/ethnicity diversity averages 0.71, and linguistic distance averages 0.49. This variation indicates that students entering doctoral programs are exposed to meaningfully different peer environments across programs and cohorts.

Table 3.2: Summary Statistics of Cohort Composition Measures

| Variable                       | Obs   | Mean | Std. Dev. | Min  | Max  |
|--------------------------------|-------|------|-----------|------|------|
| Gender Balance Index           | 4,436 | 0.61 | 0.25      | 0.00 | 1.00 |
| Race/Ethnicity Diversity Index | 4,436 | 0.71 | 0.16      | 0.00 | 0.97 |
| Language Distance              | 4,436 | 0.49 | 0.26      | 0.07 | 0.96 |

*Notes:* The minimum value of language distance is 0.07 rather than zero because cohorts composed only of U.S.-origin students are assigned a positive within-country linguistic distance, reflecting linguistic diversity within the United States.

Although the empirical analysis relies on within-program variation in cohort composition across entry cohorts, Figure 3.4 first provides descriptive background by summarizing variation at the program level. The figure plots the distribution of program-level averages for each measure and shows that cohort composition differs substantially across doctoral programs. Gender balance is broadly dispersed, race/ethnicity diversity is concentrated at relatively high values, and linguistic distance varies widely across programs, consistent with sizable differences in the communication environments students face across doctoral settings.

## 3.4 Empirical Strategy

### 3.4.1 Baseline Specification

To examine how cohort composition affects doctoral student outcomes, I estimate the following specification by ordinary least squares (OLS). For binary outcomes, the specification is interpreted as a linear probability model.

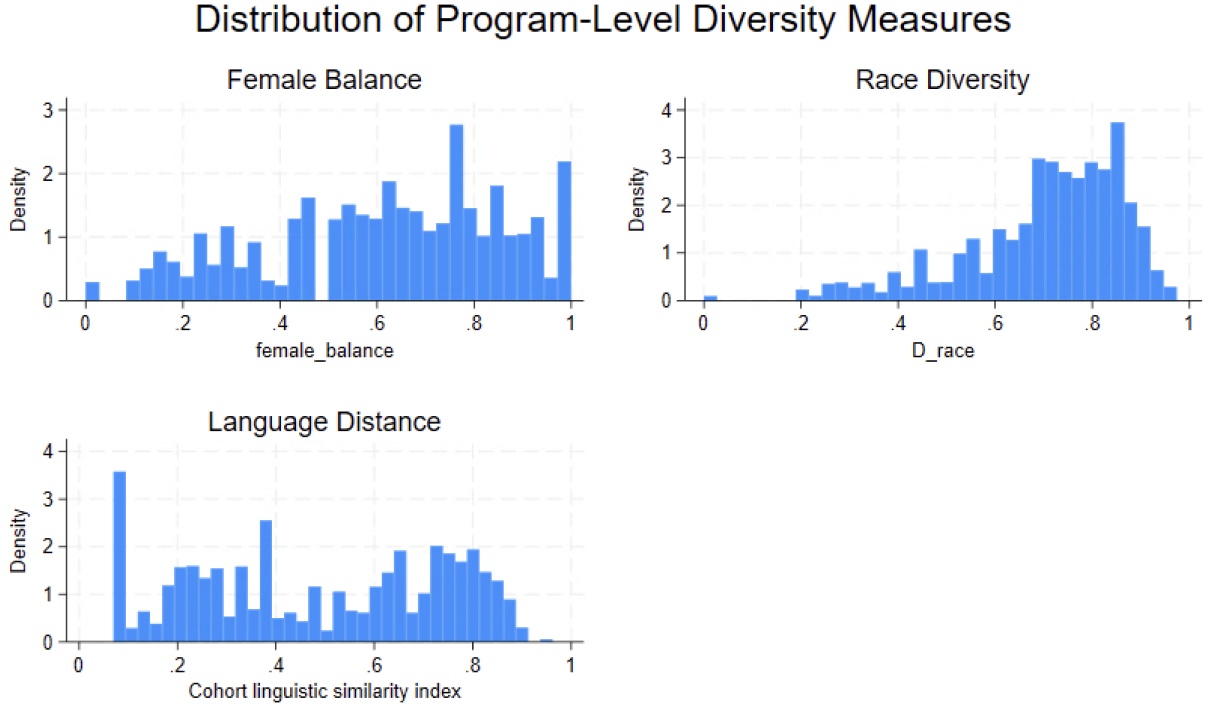


Figure 3.4: Distribution of Program-Level Diversity Measures

$$Y_{ipt} = \beta_1 \text{Gender Balance}_{pt} + \beta_2 \text{Race/Ethnicity Diversity}_{pt} + \beta_3 \text{Language Distance}_{pt} + X'_{ipt} \Gamma + \pi N_{pt} + \alpha_p + \lambda_t + \varepsilon_{ipt}, \quad (3.1)$$

where  $Y_{ipt}$  denotes the academic outcome of student  $i$  in program  $p$  and entry cohort  $t$ . The main explanatory variables are cohort-level measures of gender balance, race/ethnicity diversity, and linguistic distance, all defined at the program-by-cohort level.

The vector  $X_{ipt}$  includes individual-level controls: age, age-squared, gender, race/ethnicity, and international student status. The administrative records do not include consistently observed pre-matriculation measures of academic preparation, such as GRE scores or undergraduate GPA,<sup>11</sup> so the estimates do not condition directly on predetermined ability. The variable  $N_{pt}$  denotes cohort size and is included in all specifications to account for differences

<sup>11</sup>Undergraduate GPA is observed only for students who completed their undergraduate studies at public universities in Ohio. It is not observed for students who attended undergraduate institutions outside Ohio, abroad, or at private universities.

in the scale of peer environments across programs and entry years.

Program fixed effects,  $\alpha_p$ , absorb all time-invariant differences across doctoral programs, including persistent differences in selectivity, field characteristics, institutional resources, and program culture. Time fixed effects,  $\lambda_t$ , capture shocks common to all entering cohorts in a given year, such as macroeconomic conditions or changes in the broader higher education environment. Accordingly, identification comes from within-program changes in cohort composition over time.

The coefficients of interest,  $\beta_1$  through  $\beta_3$ , capture the relationship between each dimension of cohort composition and student outcomes, holding constant other observed characteristics and fixed differences across programs and entry years. Standard errors are clustered at the program level to account for within-program correlation in unobserved determinants of student outcomes.

This specification reflects the view that diversity in doctoral education is multidimensional. Gender balance captures whether one gender is substantially underrepresented within a cohort, while race/ethnicity diversity reflects the breadth of race/ethnicity categories represented among peers. Linguistic distance captures the degree of communication frictions that may arise in peer interactions when students come from different language backgrounds. Estimating these measures jointly is therefore useful for separating distinct dimensions of cohort composition that may otherwise be conflated in a single diversity index.

### **3.4.2 Identification Assumptions and Empirical Checks**

The empirical strategy identifies the effects of cohort diversity from within-program changes in the diversity of entering doctoral cohorts over time. The identifying assumption is that, after conditioning on program fixed effects, entry-year fixed effects, individual-level controls, and cohort size, changes in cohort diversity are orthogonal to unobserved determinants of doctoral student outcomes. In other words, within-program deviations in gender balance, racial diversity, and linguistic distance are assumed not to coincide systematically

with unobserved shocks to admissions standards, program resources, advising quality, program climate, or labor-market conditions that directly affect student outcomes.

This assumption is not directly testable. I therefore implement three empirical checks that characterize the identifying variation. First, I examine whether the diversity measures are systematically related to observable cohort characteristics. Second, I use a Monte Carlo exercise to assess whether the observed year-to-year variation in diversity within programs is comparable to the variation that would arise by chance, given each cohort’s size and each program’s overall demographic composition. Third, I examine correlations among the main diversity measures to assess whether they capture empirically distinct margins of peer diversity.

**A. Balance Tests.** I first examine whether within-program changes in cohort diversity are systematically associated with observable cohort characteristics. Table 3.3 reports estimates from separate regressions relating cohort size and average cohort age to each diversity measure, while controlling for program and entry-year fixed effects.

The balance tests provide no meaningful evidence that fluctuations in cohort diversity are systematically tied to observable changes in incoming cohort size or average age. None of the estimated relationships is statistically significant. These results do not establish the identifying assumption, but they reduce the concern that within-program changes in diversity are simply proxying for concurrent changes in unobservable cohort characteristics.

**B. Monte Carlo Simulation.** Following Lavy and Schlosser (2011), I conduct a Monte Carlo simulation to assess whether the within-program, across-cohort variation in the diversity measures is consistent with the variation that would arise from random cohort formation. The simulation provides a benchmark for evaluating whether the cohort-to-cohort changes used in the empirical analysis are unusually large or small relative to what would be expected given each program’s average demographic composition and observed cohort sizes.

For each program  $p$  and entry cohort  $t$ , I hold fixed the observed cohort size,  $n_{pt}$ . I

Table 3.3: Balance Tests Across Cohort Characteristics

|                    | Gender Balance    | Racial Diversity | Language Distance |
|--------------------|-------------------|------------------|-------------------|
| Cohort size        | -1.688<br>(1.807) | 2.802<br>(2.088) | 1.206<br>(3.010)  |
| Average cohort age | -0.131<br>(0.664) | 0.862<br>(0.642) | -0.814<br>(1.279) |
| Observations       | 276               | 276              | 276               |

*Notes:* Reported estimates are coefficients from separate cohort-level regressions. In each cell, the dependent variable is the cohort characteristic listed in the row, and the key independent variable is the peer-composition measure listed in the column. Standard errors, shown in parentheses, are clustered at the program level. All specifications include program fixed effects and entry-year fixed effects. The sample consists of 276 program-by-entry-year cohorts.

then generate simulated cohort compositions using the program-level average composition of the relevant student characteristic. This procedure preserves each program’s observed cohort-size profile while allowing the demographic composition of each simulated cohort to vary randomly according to the program’s overall composition. The simulation is conducted at the level of the underlying cohort composition, after which I reconstruct the diversity indexes used in the main analysis.

For gender balance, let  $\bar{f}_p$  denote the average female share in program  $p$ . In simulation  $s$ , the number of female students in cohort  $t$  is drawn as

$$F_{pt}^s \sim \text{Binomial}(n_{pt}, \bar{f}_p).$$

I then convert the simulated female share,  $F_{pt}^s/n_{pt}$ , into the same gender-balance index used in the main analysis. Thus, the simulation is not conducted directly on the gender-balance index itself; rather, I first simulate cohort gender composition and then reconstruct the index from the simulated composition.

For race/ethnicity and language, I use program-level average composition vectors. Let  $\bar{\mathbf{r}}_p$  denote the average race/ethnicity composition of program  $p$ , and let  $\bar{\mathbf{l}}_p$  denote the average language composition of program  $p$ . In each simulation, I draw simulated cohort-level counts

from multinomial distributions,

$$\mathbf{R}_{pt}^s \sim \text{Multinomial}(n_{pt}, \bar{\mathbf{r}}_p), \quad \mathbf{L}_{pt}^s \sim \text{Multinomial}(n_{pt}, \bar{\mathbf{l}}_p),$$

holding fixed the observed cohort size  $n_{pt}$ . The resulting simulated race/ethnicity and language compositions are then used to reconstruct the corresponding diversity indexes used in the main analysis.

For each simulated dataset, I calculate the within-program standard deviation of each diversity index across entry cohorts. Repeating this procedure 1,000 times produces, for each program and each diversity measure, a simulated distribution of within-program standard deviations. I then compare the observed within-program standard deviation with the 5th and 95th percentiles of the corresponding simulated distribution. If the observed standard deviation falls within this interval, I interpret the observed cohort-to-cohort variation as being within the range expected under the benchmark random formation process.

For many programs, the observed cohort-to-cohort variation falls within the range generated by the benchmark simulations. The observed within-program standard deviation lies within the simulated 5th–95th percentile interval for 94.6 percent of programs for gender balance, 75.0 percent for race/ethnicity diversity, and 82.1 percent for language diversity. I interpret this exercise only as a descriptive diagnostic of whether observed dispersion is unusually high or low relative to the benchmark simulations; it should not be taken as evidence that cohort composition is randomly assigned.

**C. Correlations Among Main Diversity Measures.** Finally, I examine how closely the main diversity measures move together within programs. Table 3.4 reports pairwise correlations among gender balance, racial/ethnic diversity, and language distance after removing variation explained by program fixed effects, entry-year fixed effects, and cohort size.

The correlations are small to moderate. Gender balance is only weakly related to the other two measures. Racial/ethnic diversity and language distance are more strongly related, with

a correlation of 0.285, but this relationship is far from mechanical. Overall, the table suggests that the three measures capture related but distinct dimensions of cohort composition.

Table 3.4: Residualized Correlations Among Cohort Diversity Measures

|                         | Gender Balance | Racial/Ethnic Diversity | Language Distance |
|-------------------------|----------------|-------------------------|-------------------|
| Gender Balance          | 1.000          | -                       | -                 |
| Racial/Ethnic Diversity | 0.108*         | 1.000                   | -                 |
| Language Distance       | -0.151**       | 0.285***                | 1.000             |

*Notes:* Reported entries are pairwise Pearson correlation coefficients among cohort diversity measures after netting out program fixed effects, entry-year fixed effects, and cohort size. The sample consists of 276 program-by-entry-year cohorts. Statistical significance is based on two-sided tests of zero correlation. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

## 3.5 Results

### 3.5.1 On-Time Completion

Table 3.5: Effects of Diversity Measures on 7-Year Ph.D. Completion

| Parameter        | Variable                 | 7-Year Ph.D. Completion |                          |                     |                     |
|------------------|--------------------------|-------------------------|--------------------------|---------------------|---------------------|
|                  |                          | Gender Balance          | Race/Ethnicity Diversity | Language Distance   | Full                |
|                  |                          | (1)                     | (2)                      | (3)                 | (4)                 |
| $\beta_1$        | Gender balance           | -0.021<br>(0.036)       |                          |                     | -0.025<br>(0.037)   |
| $\beta_2$        | Race/ethnicity diversity |                         | -0.150***<br>(0.052)     |                     | -0.110*<br>(0.056)  |
| $\beta_3$        | Language distance        |                         |                          | -0.200**<br>(0.078) | -0.169**<br>(0.083) |
| Observations     |                          | 4,436                   | 4,436                    | 4,436               | 4,436               |
| Program clusters |                          | 56                      | 56                       | 56                  | 56                  |

*Notes:* Estimates are from linear probability models. The dependent variable is an indicator for completing the Ph.D. within seven years. Columns (1)–(3) include gender balance, race/ethnicity diversity, and language distance separately; column (4) includes all three measures jointly. All specifications include cohort size, age, age-squared, international status, female status, race/ethnicity indicators, program fixed effects, and entry-year fixed effects. Standard errors are clustered at the program level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 3.5 presents estimates of the relationship between cohort composition and Ph.D. completion within seven years. Columns (1)–(3) estimate separate specifications that include

one cohort composition measure at a time: gender balance, racial/ethnic diversity, and language distance, respectively. Column (4) includes all three measures jointly. Gender balance has no detectable relationship with timely completion: its coefficient is small and statistically insignificant both when entered alone and when included with the other cohort composition measures. In contrast, racial/ethnic diversity and language distance are negatively related to completion. The coefficient on racial/ethnic diversity is negative and statistically significant when entered separately, and remains negative in the full specification. Language distance is also negatively related to seven-year completion and remains statistically significant after controlling for gender balance and racial/ethnic diversity.

Using the standard deviations in Table 3.2, the full specification implies that a one-standard-deviation increase in racial diversity reduces seven-year completion by 1.8 percentage points. A one-standard-deviation increase in language distance reduces completion by 4.4 percentage points. Relative to the mean completion rate of 68.2 percent, these estimates correspond to reductions of 2.6 percent and 6.4 percent, respectively. The language-distance effect is therefore more than twice as large as the racial-diversity effect. Overall, the results indicate that cohort diversity does not operate as a single construct: language composition is the dimension most strongly associated with timely completion, racial diversity also lowers completion, and gender balance has little effect.

These findings also show how the estimates documented here differ from several strands of prior work. First, the null effect of gender balance should be distinguished from estimates of same-gender or female-peer effects. For example, [Bostwick and Weinberg \(2022\)](#) show that exposure to a higher share of female peers improves outcomes for women in doctoral STEM programs. The measure used here is different: it captures balance between women and men rather than the female share itself. By construction, this measure treats under-representation of men and under-representation of women symmetrically and estimates a common effect for male and female students. The results therefore suggest that increasing gender parity in the cohort need not have the same effect as increasing the share of female peers, a distinction I examine more directly in the heterogeneity analysis below.

Second, the negative effect of racial/ethnic diversity contrasts with much of the undergraduate literature, which often finds positive effects of racial diversity on academic and longer-run outcomes (Dills, 2018; Lau, 2022). This difference suggests that the mechanisms linking racial diversity to student success may operate differently in doctoral programs. An important feature of this setting is that much of the racial diversity in doctoral cohorts is closely related to the presence of international students. However, the negative coefficient on racial diversity persists even after controlling for language distance. This suggests that the racial-diversity effect is not driven solely by linguistic heterogeneity or communication costs. Instead, it may also reflect other dimensions of cohort structure, such as peer network formation, mentoring access, social integration, or differences in program climate. Unlike undergraduate classrooms, doctoral cohorts are smaller, more persistent, and more dependent on repeated peer interaction, mentoring access, and informal academic support. Racial diversity may therefore generate different effects depending on whether it is accompanied by inclusive peer networks and supportive program climates. I return to this issue in the heterogeneity analysis, including the analysis by student group and the analysis by STEM status in the heterogeneity analyses below

Finally, the negative estimate for language distance is consistent with prior work on language frictions in economic and organizational settings, including theoretical work on common language and culture and evidence from multinational teams (Lazear, 1999; Tenzer et al., 2014). This result supports the interpretation that linguistic heterogeneity can impede the peer interactions through which students acquire information, receive academic support, and integrate into doctoral programs. Taken together, the racial-diversity and language-distance estimates suggest that communication barriers are an important part of the story, but they do not fully account for the relationship between racial diversity and timely completion. The next section examines whether these average effects mask important heterogeneity across students and program environments.

**Heterogeneity Analysis.** To examine heterogeneous effects, I interact each cohort-level composition measure with the individual characteristic most closely related to that dimension. Specifically, gender balance is interacted with an indicator for female students, race diversity is interacted with an indicator for non-White students, and language distance is interacted with an indicator for international students. The estimating equation is:

$$\begin{aligned}
PhDin7_{ipt} = & \beta_0 + \beta_1 FemaleBalance_{pt} + \beta_2 RaceDiversity_{pt} + \beta_3 LanguageDistance_{pt} \\
& + \gamma_1 Female_i + \gamma_2 NonWhite_i + \gamma_3 International_i \\
& + \delta_1 (FemaleBalance_{pt} \times Female_i) \\
& + \delta_2 (RaceDiversity_{pt} \times NonWhite_i) \\
& + \delta_3 (LanguageDistance_{pt} \times International_i) \\
& + X'_{ipt} \Gamma + \pi N_{pt} + \alpha_p + \lambda_t + \varepsilon_{ipt}.
\end{aligned} \tag{3.2}$$

In this specification, the coefficients on the cohort-level composition measures,  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$ , capture the association between each diversity measure and Ph.D. completion for the reference group: male students for gender balance, White students for race/ethnicity diversity, and domestic students for language distance. The interaction coefficients,  $\delta_1$ ,  $\delta_2$ , and  $\delta_3$ , indicate whether these associations differ for female, non-White, and international students, respectively. Thus, the total estimated effect of Gender balance for female students is  $\beta_1 + \delta_1$ , the total estimated effect of race/ethnicity diversity for non-White students is  $\beta_2 + \delta_2$ , and the total estimated effect of language distance for international students is  $\beta_3 + \delta_3$ .

Table 3.6 examines whether the effects of cohort composition differ across student groups. The estimates show limited heterogeneity in the effect of gender balance: the coefficient is negative for male students and close to zero for female students, but neither estimate is statistically significant. In contrast, the effect of racial diversity is concentrated among

Table 3.6: Heterogeneous Effects of Cohort Composition on 7-Year Ph.D. Completion

| Parameter                                | Effect                                | Ph.D. Completion<br>within 7 Years |
|------------------------------------------|---------------------------------------|------------------------------------|
| <i>Panel A. Gender Balance</i>           |                                       |                                    |
| $\beta_1$                                | Male students                         | -0.059<br>(0.045)                  |
| $\delta_1$                               | Difference for female students        | 0.067<br>(0.069)                   |
| $\beta_1 + \delta_1$                     | Female students                       | 0.008<br>(0.057)                   |
| <i>Panel B. Race/Ethnicity Diversity</i> |                                       |                                    |
| $\beta_2$                                | White students                        | -0.072<br>(0.066)                  |
| $\delta_2$                               | Difference for non-White students     | -0.097<br>(0.094)                  |
| $\beta_2 + \delta_2$                     | Non-White students                    | -0.169**<br>(0.077)                |
| <i>Panel C. Language Distance</i>        |                                       |                                    |
| $\beta_3$                                | Domestic students                     | -0.168*<br>(0.089)                 |
| $\delta_3$                               | Difference for international students | -0.046<br>(0.079)                  |
| $\beta_3 + \delta_3$                     | International students                | -0.214**<br>(0.100)                |
| Observations                             |                                       | 4,436                              |
| Program clusters                         |                                       | 56                                 |

*Notes:* Estimates are from linear probability models. The dependent variable is an indicator for completing the Ph.D. within seven years. The table reports group-specific marginal effects implied by interaction models. For each diversity measure, the first row reports the estimated association for the reference group, the second row reports the difference for the comparison group, and the third row reports the sum of the main effect and interaction term. All specifications include gender balance, race/ethnicity diversity, language distance, the relevant interaction terms, cohort size, age, age-squared, international status, female status, race/ethnicity indicators, program fixed effects, and entry-year fixed effects. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

non-White students. A more racially diverse cohort reduces seven-year completion for non-White students, while the corresponding effect for White students is smaller and statistically insignificant. Language distance reduces completion for both domestic and international students, with a larger point estimate for international students.

These results indicate that the negative association between racial diversity and Ph.D. completion is concentrated among non-White students. This finding should not be interpreted as evidence that diversity itself is harmful. Rather, the racial-diversity measure may capture several features of cohort organization that are correlated with racial composition, including same-group peer availability, peer network formation, mentoring access, social integration, or program climate. The estimates therefore point to these mechanisms as possible channels, but they do not distinguish among them directly. By contrast, language distance lowers completion for both domestic and international students, a pattern more consistent with communication frictions affecting the cohort as a whole.

**Nonlinearity Analysis.** To examine whether diversity effects vary across the distribution, I estimate a linear spline specification with one knot at the sample median of each diversity measure.<sup>12</sup> The median knot provides an empirical split between lower and higher diversity ranges, rather than a theoretically sharp threshold. The estimating equation is:

$$\begin{aligned}
PhDin7_{ipt} = & \beta_0 + \beta_1 FemaleBalance_{pt} + \beta_2 (FemaleBalance_{pt} - \kappa_F)_+ \\
& + \theta_1 RaceDiversity_{pt} + \theta_2 (RaceDiversity_{pt} - \kappa_R)_+ \\
& + \phi_1 LanguageDistance_{pt} + \phi_2 (LanguageDistance_{pt} - \kappa_L)_+ \\
& + \pi N_{pt} + X'_{ipt} \Gamma + \alpha_p + \lambda_t + \varepsilon_{ipt}.
\end{aligned} \tag{3.3}$$

Here,  $\kappa_F$ ,  $\kappa_R$ , and  $\kappa_L$  denote the sample median knots for female balance, race/ethnicity diversity, and language distance, respectively. The operator  $(x - \kappa)_+$  is defined as  $\max(x -$

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<sup>12</sup>The sample median knots are  $\kappa_F = 0.648$  for female balance,  $\kappa_R = 0.738$  for race/ethnicity diversity, and  $\kappa_L = 0.567$  for language distance.

$\kappa, 0$ ), so the spline term equals zero below the knot and increases linearly above the knot. This specification allows the slope of each diversity measure to change after its median while maintaining continuity in the fitted relationship at the knot.

The coefficients  $\beta_1$ ,  $\theta_1$ , and  $\phi_1$  capture the slopes of female balance, race/ethnicity diversity, and language distance below their respective knots. The slopes above the knots are given by  $\beta_1 + \beta_2$ ,  $\theta_1 + \theta_2$ , and  $\phi_1 + \phi_2$ , respectively. Thus,  $\beta_2$ ,  $\theta_2$ , and  $\phi_2$  capture the change in slope after the median knot. All specifications include the same individual-level controls, fixed effects, and clustered standard errors as in the baseline model.

Table 3.7 reports the estimated spline coefficients and the implied marginal effects below and above the median knot for each diversity measure. For gender balance, neither the slope below the median nor the slope above the median is statistically significant, and the change in slope above the median knot is also insignificant. This provides little evidence that the association between gender balance and doctoral completion varies meaningfully across the distribution of gender balance.

For race/ethnicity diversity, the slope below the median knot is negative and statistically significant, indicating that increases in race/ethnicity diversity are associated with lower Ph.D. completion rates among cohorts that are still relatively low in racial diversity. One possible interpretation is that increases from a highly homogeneous baseline may not yet generate the benefits of a diverse peer environment. Instead, they may reflect cohorts in which underrepresented students remain relatively isolated, without sufficient critical mass or institutional support to reduce social and academic barriers. In this setting, diversity may increase exposure to difference before the cohort has enough representation or inclusion infrastructure for students to benefit from broader peer networks. Above the median knot, however, the implied slope is close to zero and statistically insignificant, suggesting that the negative association does not persist at higher levels of racial diversity.

For language distance, the below-median slope is negative but statistically insignificant, while the implied slope above the median knot is negative and statistically significant. This pattern suggests that linguistic heterogeneity becomes more consequential once language

Table 3.7: Nonlinear Effects Using Linear Spline Specification

| Parameter                                | Spline Component                  | 7-Year Ph.D.<br>Completion |
|------------------------------------------|-----------------------------------|----------------------------|
| <i>Panel A. Gender Balance</i>           |                                   |                            |
| $\beta_1$                                | Below-median slope                | 0.007<br>(0.067)           |
| $\beta_2$                                | Change in slope above median knot | -0.074<br>(0.121)          |
| $\beta_1 + \beta_2$                      | Above-median slope                | -0.068<br>(0.076)          |
| <i>Panel B. Race/Ethnicity Diversity</i> |                                   |                            |
| $\theta_1$                               | Below-median slope                | -0.158**<br>(0.077)        |
| $\theta_2$                               | Change in slope above median knot | 0.134<br>(0.255)           |
| $\theta_1 + \theta_2$                    | Above-median slope                | -0.025<br>(0.209)          |
| <i>Panel C. Language Distance</i>        |                                   |                            |
| $\phi_1$                                 | Below-median slope                | -0.085<br>(0.127)          |
| $\phi_2$                                 | Change in slope above median knot | -0.206<br>(0.212)          |
| $\phi_1 + \phi_2$                        | Above-median slope                | -0.291**<br>(0.139)        |
| Observations                             |                                   | 4,436                      |
| Program clusters                         |                                   | 56                         |

*Notes:* Estimates are from linear probability models. The dependent variable is an indicator for completing the Ph.D. within seven years. The table reports estimates from linear spline specifications with one knot placed at the sample median of each diversity measure. Parameters  $\beta_1$ ,  $\theta_1$ , and  $\phi_1$  are the below-median slopes. Parameters  $\beta_2$ ,  $\theta_2$ , and  $\phi_2$  are changes in slope above the median knots. The sums  $\beta_1 + \beta_2$ ,  $\theta_1 + \theta_2$ , and  $\phi_1 + \phi_2$  are the implied above-median slopes. All specifications include gender balance, race/ethnicity diversity, language distance, the corresponding spline terms, cohort size, age, age-squared, international status, female status, race/ethnicity indicators, program fixed effects, and entry-year fixed effects. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

distance is already relatively high. In more linguistically distant cohorts, additional language distance may increase communication frictions, reduce ease of peer collaboration, or make it more difficult for students to form informal academic support networks. Overall, the spline results suggest that the relationship between diversity and Ph.D. completion is not uniform across the distribution: the clearest nonlinear patterns are the negative association between race/ethnicity diversity and completion below the median knot and the negative association between language distance and completion above the median knot.

**STEM vs. Non-STEM Programs.** Table 3.8 reports the mean and standard deviation of the main cohort-composition measures separately for STEM and non-STEM programs, and Figure 3.5 plots the corresponding distributions. The descriptive patterns show that non-STEM programs have higher average gender balance, indicating that their cohorts are closer to gender parity. By contrast, STEM programs have higher average race/ethnicity diversity, language distance, and international-student share. The difference is especially pronounced for language-related measures: STEM programs have both a substantially higher mean language distance and a much larger share of international students. The histograms similarly show that the STEM distribution is shifted toward higher values of language distance, while non-STEM programs are more concentrated at lower levels. This pattern should be interpreted descriptively, since the higher language-distance values in STEM may partly reflect the larger presence of international students rather than greater linguistic dispersion conditional on international enrollment.

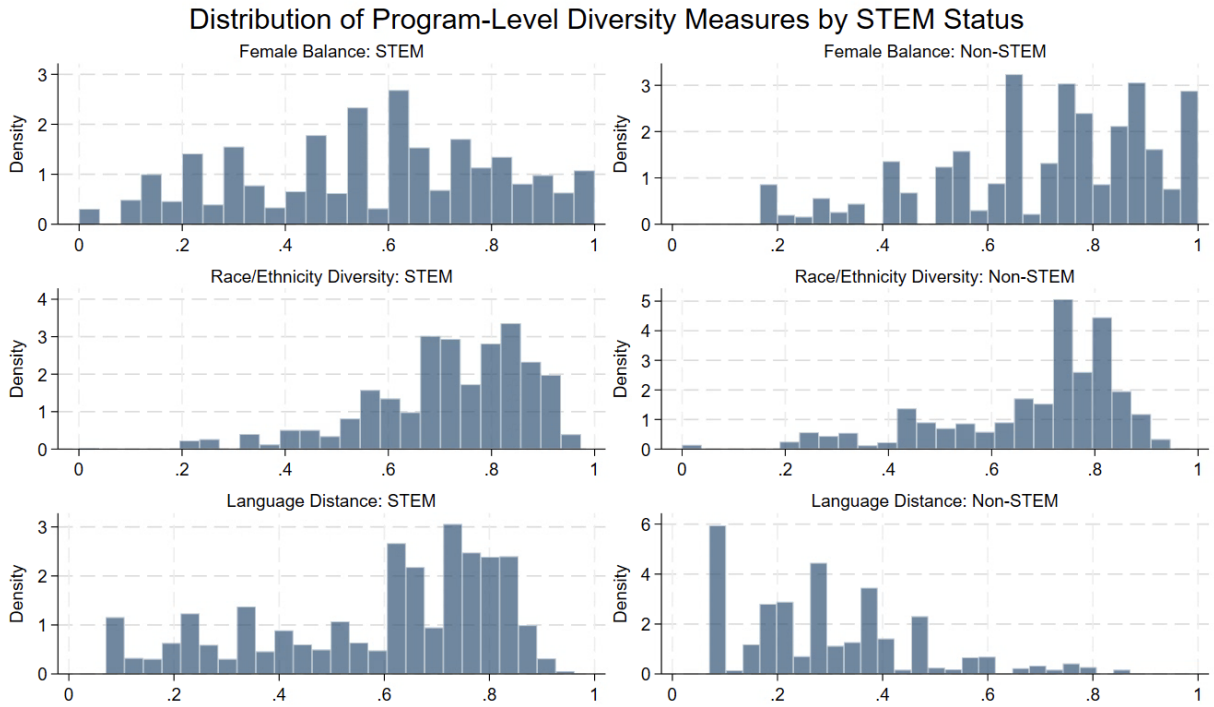
Table 3.9 reports the effects of diversity measures on 7-year Ph.D. completion estimated separately for STEM and non-STEM programs. In STEM programs, language distance is negatively and statistically significantly associated with completing the Ph.D. within seven years. This pattern is consistent with the nonlinear estimates in Table 3.7, which show that the negative association between language distance and completion is concentrated above the median language-distance knot. Because STEM programs have higher average language distance and their distribution is shifted toward higher language-distance values, STEM

Table 3.8: Summary Statistics by STEM Status

| Variable                 | STEM  |           | Non-STEM |           |
|--------------------------|-------|-----------|----------|-----------|
|                          | Mean  | Std. Dev. | Mean     | Std. Dev. |
| Gender Balance           | 0.562 | 0.248     | 0.712    | 0.210     |
| Race/ethnicity Diversity | 0.719 | 0.156     | 0.680    | 0.175     |
| Language Distance        | 0.590 | 0.231     | 0.293    | 0.176     |
| International Share      | 0.495 | 0.500     | 0.178    | 0.383     |
| Observations             | 2,934 |           | 1,502    |           |

*Notes:* The table reports summary statistics separately for STEM and non-STEM programs.

Figure 3.5: Distribution of Program-Level Diversity Measures by STEM Status



cohorts are more likely to fall in the part of the distribution where language distance is most strongly associated with lower completion. In contrast, the coefficient on language distance is also negative for non-STEM programs but is smaller and not statistically significant. These results suggest that the STEM/non-STEM difference may partly reflect where programs lie in the language-distance distribution, rather than a fundamentally different mechanism across fields.

Table 3.9: Effects of Diversity Measures on 7-Year Ph.D. Completion by STEM Status

| Parameter        | Variable                 | 7-Year Ph.D. Completion |                     |
|------------------|--------------------------|-------------------------|---------------------|
|                  |                          | STEM                    | Non-STEM            |
| $\beta_1$        | Gender balance           | -0.020<br>(0.039)       | 0.050<br>(0.080)    |
| $\beta_2$        | Race/ethnicity diversity | -0.031<br>(0.071)       | -0.219**<br>(0.096) |
| $\beta_3$        | Language distance        | -0.221**<br>(0.090)     | -0.081<br>(0.136)   |
| Observations     |                          | 2,934                   | 1,502               |
| Program clusters |                          | 35                      | 21                  |

*Notes:* Estimates are from linear probability models. The dependent variable is an indicator for completing the Ph.D. within seven years. The table reports estimates from separate regressions for STEM and non-STEM students. Each specification includes gender balance, race/ethnicity diversity, language distance, cohort size, age, age-squared, international status, female status, race/ethnicity indicators, program fixed effects, and entry-year fixed effects. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

For non-STEM programs, race/ethnicity diversity is negatively and significantly associated with 7-year Ph.D. completion. The coefficient indicates that higher racial diversity within the cohort is related to a lower probability of completing the Ph.D. within seven years. By contrast, race/ethnicity diversity is not statistically significant among STEM programs.

## 3.6 Mechanism Analysis

### 3.6.1 Dropout by Year

The completion results indicate that cohort diversity lowers timely Ph.D. completion along specific dimensions, especially language distance and racial diversity. To examine whether these effects operate through early exit from doctoral programs, I re-estimate Equation 3.1, replacing the dependent variable with an indicator for cumulative dropout by each year of doctoral study. This specification uses the same controls, fixed effects, and clustering structure as the baseline model. The exercise shows when diversity affects persistence and helps distinguish early-program attrition from delays among students who remain enrolled.

Table 3.10 reports estimates from specifications that use cumulative dropout by each year of doctoral study as the dependent variable, with separate columns for dropout by the end of years 1 through 6. Language distance is positively associated with cumulative dropout throughout the early years of doctoral study. A one-standard-deviation (0.26) increase in language distance raises the probability of dropout by about 1.4 percentage points by the end of the first year and by about 3.8 percentage points by the end of the third year. The estimated effect remains large and statistically significant through years 4 and 5, before declining somewhat and becoming statistically insignificant by year 6. This timing suggests that language distance is most strongly associated with persistence during the early and middle stages of doctoral training, when students complete coursework, prepare for exams, and form peer and advising networks.

Table 3.10: Heterogeneous Effects of Diversity Measures on Dropout by Year

| Parameter                                | Effect                                | Dropout by Year    |                    |                    |                    |                   |                   |
|------------------------------------------|---------------------------------------|--------------------|--------------------|--------------------|--------------------|-------------------|-------------------|
|                                          |                                       | Year 1             | Year 2             | Year 3             | Year 4             | Year 5            | Year 6            |
| <i>Panel A. Gender Balance</i>           |                                       |                    |                    |                    |                    |                   |                   |
| $\beta_1$                                | Male students                         | 0.018<br>(0.022)   | 0.034<br>(0.032)   | 0.019<br>(0.040)   | 0.040<br>(0.043)   | 0.038<br>(0.044)  | 0.037<br>(0.045)  |
| $\delta_1$                               | Difference for female students        | -0.039<br>(0.035)  | -0.047<br>(0.048)  | -0.017<br>(0.057)  | -0.044<br>(0.058)  | -0.058<br>(0.060) | -0.057<br>(0.060) |
| $\beta_1 + \delta_1$                     | Female students                       | -0.021<br>(0.034)  | -0.013<br>(0.044)  | 0.003<br>(0.049)   | -0.004<br>(0.049)  | -0.021<br>(0.048) | -0.021<br>(0.049) |
| <i>Panel B. Race/Ethnicity Diversity</i> |                                       |                    |                    |                    |                    |                   |                   |
| $\beta_2$                                | White students                        | 0.027<br>(0.028)   | 0.045<br>(0.045)   | 0.059<br>(0.055)   | 0.045<br>(0.061)   | 0.063<br>(0.062)  | 0.069<br>(0.066)  |
| $\delta_2$                               | Difference for non-White students     | 0.029<br>(0.045)   | 0.014<br>(0.067)   | 0.035<br>(0.080)   | 0.028<br>(0.089)   | 0.035<br>(0.091)  | 0.025<br>(0.094)  |
| $\beta_2 + \delta_2$                     | Non-White students                    | 0.056<br>(0.043)   | 0.059<br>(0.059)   | 0.094<br>(0.069)   | 0.074<br>(0.078)   | 0.098<br>(0.075)  | 0.094<br>(0.075)  |
| <i>Panel C. Language Distance</i>        |                                       |                    |                    |                    |                    |                   |                   |
| $\beta_3$                                | Domestic students                     | 0.042<br>(0.031)   | 0.066<br>(0.046)   | 0.139**<br>(0.065) | 0.139*<br>(0.072)  | 0.114<br>(0.071)  | 0.100<br>(0.073)  |
| $\delta_3$                               | Difference for international students | 0.051<br>(0.036)   | 0.056<br>(0.056)   | 0.045<br>(0.064)   | 0.047<br>(0.067)   | 0.054<br>(0.068)  | 0.063<br>(0.071)  |
| $\beta_3 + \delta_3$                     | International students                | 0.093**<br>(0.040) | 0.121**<br>(0.055) | 0.184**<br>(0.072) | 0.186**<br>(0.079) | 0.168*<br>(0.085) | 0.163*<br>(0.087) |
| $\Delta(\beta_3 + \delta_3)$             | Change from previous year             | 0.093              | 0.029              | 0.063              | 0.002              | -0.018            | -0.006            |
| Observations                             |                                       | 4,436              | 4,436              | 4,436              | 4,436              | 4,436             | 4,436             |
| Program clusters                         |                                       | 56                 | 56                 | 56                 | 56                 | 56                | 56                |

*Notes:* Estimates are from linear probability models. The dependent variable in each column is an indicator for dropping out by the indicated year after initial enrollment. For each diversity measure, the first row reports the estimated association for the reference group, the second row reports the difference for the comparison group, and the third row reports the total marginal effect for the comparison group. Each specification includes gender balance, race/ethnicity diversity, language distance, the relevant interaction terms, cohort size, age, age-squared, international status, female status, race/ethnicity indicators, program fixed effects, and entry-year fixed effects. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

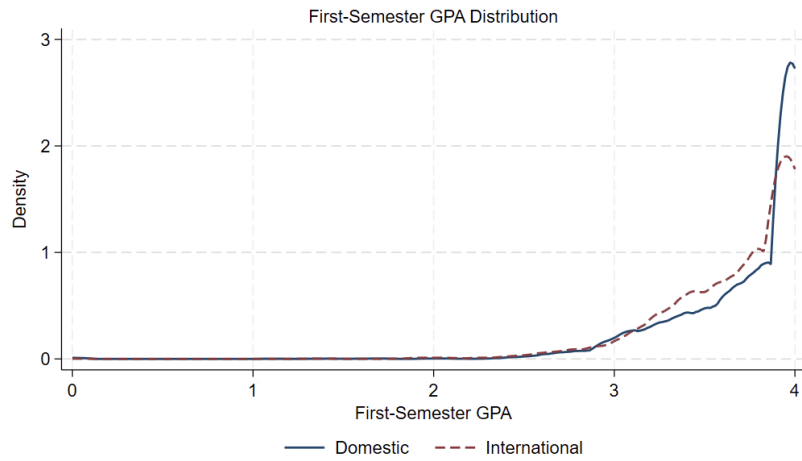
In contrast, the dropout specifications provide little evidence that racial diversity increases attrition from doctoral programs. The estimates are imprecise and cannot be distinguished from zero, suggesting that the negative association between racial diversity and seven-year completion documented in Table 3.5 is more likely to reflect delayed degree completion among students who remain enrolled rather than elevated dropout. Gender balance, similarly, shows no detectable association with dropout at any point in the program.

### 3.6.2 Grades

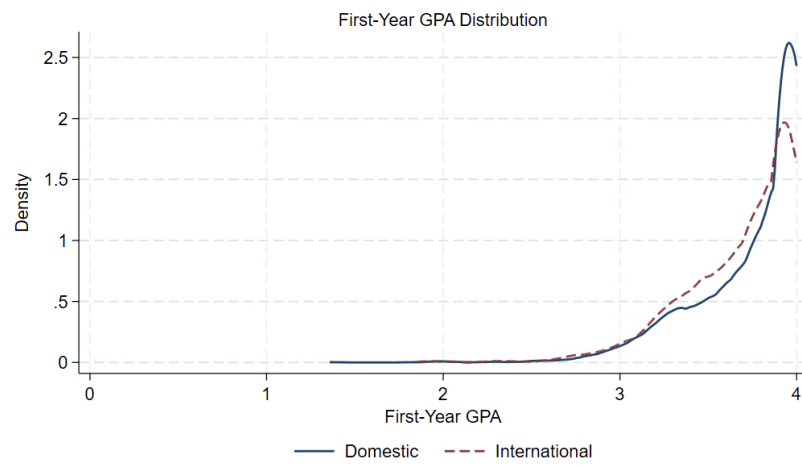
I next examine whether cohort diversity is associated with short-run academic performance. GPA is a natural intermediate outcome because much of the undergraduate diversity literature focuses on academic achievement and classroom performance. In doctoral programs, however, GPA may be a less informative margin of progress. Figure 3.6 shows that first-semester, first-year, and final GPAs are all highly concentrated near 4.0 for both domestic and international students, leaving relatively little variation for cohort diversity to explain. This compression is especially important for interpreting the GPA results below: a weak association between cohort diversity and GPA need not imply that cohort composition is irrelevant, but rather that GPA may not capture the main margins through which peer environments affect doctoral progress.

To assess this channel, Table 3.11 re-estimates Equation 3.2 using first-year GPA and cumulative doctoral GPA as dependent variables. I interpret these specifications as potential mechanism analysis: if cohort diversity affects doctoral completion primarily by reducing course performance, the peer-composition measures should also predict GPA. Table 3.11 reports estimates separately across student groups to examine whether any GPA response is concentrated among particular students.

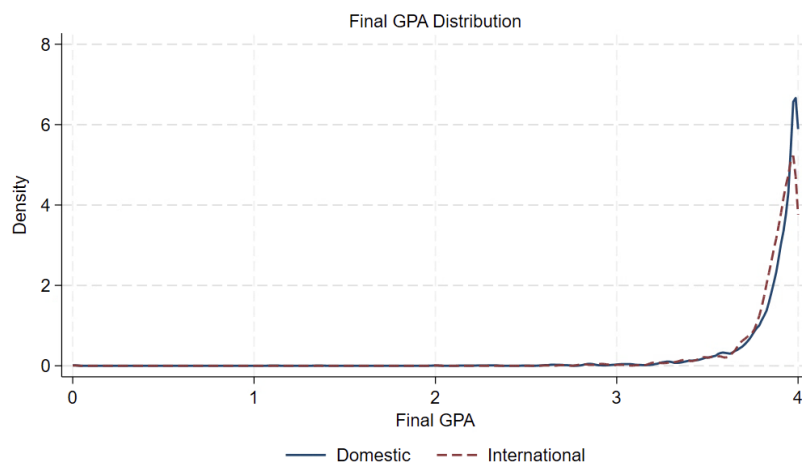
The results provide little evidence that cohort diversity operates through measured course performance. The estimates for gender balance are small and imprecise across groups. Racial diversity has opposite-signed estimates for White and non-White students, and language



(a) First-semester GPA



(b) First-year GPA



(c) Final GPA

Figure 3.6: GPA Distributions by International Status

Table 3.11: Heterogeneous Effects of Cohort Composition on Academic Performance

| Parameter                                | Effect                                | First-Semester<br>GPA | First-Year<br>GPA   | Final<br>GPA      |
|------------------------------------------|---------------------------------------|-----------------------|---------------------|-------------------|
| <i>Panel A. Gender Balance</i>           |                                       |                       |                     |                   |
| $\beta_1$                                | Male students                         | 0.043<br>(0.045)      | 0.041<br>(0.031)    | -0.017<br>(0.029) |
| $\delta_1$                               | Difference for female students        | -0.046<br>(0.046)     | -0.075*<br>(0.038)  | -0.028<br>(0.032) |
| $\beta_1 + \delta_1$                     | Female students                       | -0.003<br>(0.047)     | -0.034<br>(0.034)   | -0.045<br>(0.032) |
| <i>Panel B. Race/Ethnicity Diversity</i> |                                       |                       |                     |                   |
| $\beta_2$                                | White students                        | 0.034<br>(0.054)      | 0.074<br>(0.044)    | 0.011<br>(0.031)  |
| $\delta_2$                               | Difference for non-White students     | -0.074<br>(0.080)     | -0.116*<br>(0.063)  | -0.014<br>(0.040) |
| $\beta_2 + \delta_2$                     | Non-White students                    | -0.040<br>(0.067)     | -0.042<br>(0.060)   | -0.003<br>(0.036) |
| <i>Panel C. Language Distance</i>        |                                       |                       |                     |                   |
| $\beta_3$                                | Domestic students                     | -0.121<br>(0.090)     | -0.124**<br>(0.062) | -0.054<br>(0.051) |
| $\delta_3$                               | Difference for international students | 0.049<br>(0.072)      | 0.055<br>(0.065)    | 0.020<br>(0.041)  |
| $\beta_3 + \delta_3$                     | International students                | -0.072<br>(0.101)     | -0.069<br>(0.070)   | -0.034<br>(0.054) |
| Observations                             |                                       | 4,436                 | 4,296               | 4,436             |
| Program clusters                         |                                       | 56                    | 56                  | 56                |

*Notes:* Estimates are from linear models. The dependent variables are GPA outcomes. The table reports group-specific marginal effects implied by interaction models. Difference rows report the interaction coefficient for the comparison group relative to the reference group. All specifications include cohort size, age, age-squared, international status, female status, race/ethnicity indicators, program fixed effects, and entry-year fixed effects. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

distance is more negative for domestic than for international students, especially for first-year GPA, but these patterns are not estimated precisely enough to support strong conclusions. Overall, GPA does not appear to be the primary short-run mechanism linking cohort diversity to doctoral completion. The evidence instead points toward margins outside measured course performance, such as persistence, integration, advising access, peer networks, or delays in progress toward degree completion.

## 3.7 Additional Analyses and Robustness Checks

This section examines whether the main results are sensitive to alternative ways of measuring cohort composition and to sample restrictions. The analyses serve three purposes. First, I distinguish the effects of group shares from the effects of diversity or distance within the cohort. Second, I examine whether the baseline patterns are driven by particular demographic components, such as racial heterogeneity among domestic or international students. Third, I assess whether the estimates depend on the minimum cohort-size restriction used in the main analysis.

### 3.7.1 Alternative Peer-Composition Measures

The baseline specifications use cohort-level measures that capture balance, fractionalization, and linguistic distance. These measures are intended to summarize the structure of the peer environment rather than the representation of any single group. As an alternative, Table 3.12 replaces these indices with simple leave-one-out peer-share measures: the share of other students in the entering cohort who are female, non-White, and international, excluding the focal student from both the numerator and denominator.

The estimates provide little evidence that seven-year Ph.D. completion declines mechanically as the share of female, non-White, or international peers rises. The female-peer share is positive in all specifications, although imprecisely estimated. The non-White share is nega-

tive when included alone but becomes close to zero in the full specification. The international-peer share is negative and marginally significant when entered separately, but the estimate becomes smaller and statistically insignificant once the other peer-share measures are included. These results suggest that the baseline findings are not simply driven by the size of any single demographic group.

Table 3.13 asks whether these peer-share effects differ by student type. The only suggestive heterogeneity appears for female-peer exposure: the estimated effect is larger for female students than for male students and is marginally significant. This pattern is consistent with evidence that same-gender peers can affect graduate outcomes through representation, belonging, and peer support (Bostwick and Weinberg, 2022). By contrast, non-White peer share has little relationship with completion for either White or non-White students, and international peer share has similar estimates for domestic and international students.

These alternative specifications clarify the interpretation of the main diversity measures. A higher group share does not necessarily imply that a cohort is more balanced, more fragmented, or more difficult to navigate. Share measures capture representation, whereas diversity and distance measures capture how students are distributed across groups and the extent to which peer interactions may involve demographic or linguistic barriers. The evidence therefore supports interpreting the baseline measures as features of the cohort environment rather than as simple group-size effects.

### 3.7.2 Heterogeneity by STEM Status

Table 3.14 examines whether the effects of the cohort-composition measures differ between STEM and non-STEM programs. This distinction is important because doctoral training is organized differently across fields (Golde, 2005). STEM programs are more likely to involve lab-based research groups, externally funded assistantships, and structured research teams, whereas many non-STEM programs rely more heavily on individualized advising relationships and less formal peer networks (Flores-Scott and Nerad, 2012).

Table 3.12: Alternative Peer-Composition Measures and 7-Year Ph.D. Completion

| Parameter        | Peer-Composition Measure | 7-Year Ph.D. Completion |                   |                     |                   |
|------------------|--------------------------|-------------------------|-------------------|---------------------|-------------------|
|                  |                          | Female Share            | Non-White Share   | International Share | Full              |
|                  |                          | (1)                     | (2)               | (3)                 | (4)               |
| $\beta_1$        | Female share             | 0.097<br>(0.066)        |                   |                     | 0.091<br>(0.065)  |
| $\beta_2$        | Non-White share          |                         | -0.094<br>(0.065) |                     | -0.009<br>(0.081) |
| $\beta_3$        | International share      |                         |                   | -0.142*<br>(0.072)  | -0.131<br>(0.092) |
| Observations     |                          | 4,436                   | 4,436             | 4,436               | 4,436             |
| Program clusters |                          | 56                      | 56                | 56                  | 56                |

*Notes:* Estimates are from linear probability models. The dependent variable is an indicator for completing the Ph.D. within seven years. Columns (1)–(3) include female share, non-White share, and international share separately; column (4) includes all three measures jointly. All specifications include the same controls and fixed effects as the baseline specification. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

The estimates show no evidence that gender balance affects seven-year completion in either STEM or non-STEM programs. The coefficients are small and statistically insignificant for both male and female students. Race/ethnicity diversity, however, displays a more pronounced pattern in non-STEM fields. In STEM programs, the estimates are not statistically significant for either White or non-White students. In non-STEM programs, race/ethnicity diversity is negatively associated with completion for both groups, with the larger and statistically significant estimate appearing for non-White students.

Linguistic distance shows a different pattern. In STEM programs, linguistic distance is negatively and significantly associated with completion for both domestic and international students, with a larger estimate for international students. In non-STEM programs, the coefficients are also negative but less precisely estimated. Taken together, these results indicate that different dimensions of cohort composition matter in different institutional settings. Race/ethnicity diversity appears more consequential in non-STEM programs, while linguistic distance is more strongly related to completion in STEM programs.

Table 3.13: Heterogeneous Effects of Peer-Composition Measures on 7-Year Ph.D. Completion

| Parameter                           | Effect                                | 7-Year Ph.D.<br>Completion |
|-------------------------------------|---------------------------------------|----------------------------|
| <i>Panel A. Female Peers</i>        |                                       |                            |
| $\beta_1$                           | Male students                         | 0.027<br>(0.069)           |
| $\delta_1$                          | Difference for female students        | 0.125*<br>(0.066)          |
| $\beta_1 + \delta_1$                | Female students                       | 0.152*<br>(0.079)          |
| <i>Panel B. Non-White Share</i>     |                                       |                            |
| $\beta_2$                           | White students                        | -0.002<br>(0.082)          |
| $\delta_2$                          | Difference for non-White students     | -0.000<br>(0.081)          |
| $\beta_2 + \delta_2$                | Non-White students                    | -0.003<br>(0.099)          |
| <i>Panel C. International Peers</i> |                                       |                            |
| $\beta_3$                           | Domestic students                     | -0.148<br>(0.096)          |
| $\delta_3$                          | Difference for international students | 0.023<br>(0.073)           |
| $\beta_3 + \delta_3$                | International students                | -0.125<br>(0.102)          |
| Observations                        |                                       | 4,436                      |
| Program clusters                    |                                       | 56                         |

*Notes:* Estimates are from linear probability models. The dependent variable is an indicator for completing the Ph.D. within seven years. For each peer-composition measure, the first row reports the reference-group effect, the second row reports the interaction effect, and the third row reports the total marginal effect for the comparison group. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table 3.14: Heterogeneous Effects by STEM Status

| Parameter                                | Effect                                | 7-Year Ph.D. Completion |                     |
|------------------------------------------|---------------------------------------|-------------------------|---------------------|
|                                          |                                       | STEM                    | Non-STEM            |
| <i>Panel A. Gender Balance</i>           |                                       |                         |                     |
| $\beta_1$                                | Male students                         | 0.014<br>(0.038)        | -0.158<br>(0.133)   |
| $\delta_1$                               | Difference for female students        | 0.001<br>(0.067)        | 0.162<br>(0.159)    |
| $\beta_1 + \delta_1$                     | Female students                       | 0.014<br>(0.069)        | 0.004<br>(0.093)    |
| <i>Panel B. Race/Ethnicity Diversity</i> |                                       |                         |                     |
| $\beta_2$                                | White students                        | 0.031<br>(0.094)        | -0.180*<br>(0.097)  |
| $\delta_2$                               | Difference for non-White students     | -0.117<br>(0.114)       | -0.247<br>(0.197)   |
| $\beta_2 + \delta_2$                     | Non-White students                    | -0.086<br>(0.082)       | -0.426**<br>(0.184) |
| <i>Panel C. Language Distance</i>        |                                       |                         |                     |
| $\beta_3$                                | Domestic students                     | -0.215**<br>(0.099)     | -0.059<br>(0.148)   |
| $\delta_3$                               | Difference for international students | -0.074<br>(0.087)       | -0.117<br>(0.210)   |
| $\beta_3 + \delta_3$                     | International students                | -0.289***<br>(0.102)    | -0.176<br>(0.217)   |
| Observations                             |                                       | 2,934                   | 1,502               |
| Program clusters                         |                                       | 35                      | 21                  |

*Notes:* Estimates are from linear probability models. The dependent variable is an indicator for completing the Ph.D. within seven years. The table reports group-specific marginal effects implied by interaction models estimated separately for STEM and non-STEM students. For each diversity measure, the first row reports the estimated association for the reference group, the second row reports the difference for the comparison group, and the third row reports the sum of the main effect and interaction term. All specifications include gender balance, race/ethnicity diversity, language distance, the relevant interaction terms, cohort size, age, age-squared, international status, female status, race/ethnicity indicators, program fixed effects, and entry-year fixed effects. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

### 3.7.3 Race/ethnicity Diversity Among Domestic and International Students

The baseline race/ethnicity diversity measure combines racial heterogeneity across all students in the cohort. To examine whether the results are driven by racial heterogeneity within particular student groups, I decompose race/ethnicity diversity into domestic and international components. Table 3.15 shows that both measures vary substantially across cohorts, with domestic race/ethnicity diversity somewhat higher on average than international race/ethnicity diversity.

Table 3.16 indicates that the two measures capture distinct dimensions of cohort composition. The correlation between domestic and international race/ethnicity diversity is close to zero, implying that cohorts with greater racial heterogeneity among domestic students are not necessarily more racially heterogeneous among international students. This motivates estimating their associations with completion separately.

Table 3.17 reports the completion results. Neither domestic race/ethnicity diversity nor international race/ethnicity diversity is statistically significant, whether entered separately or jointly. The estimates are small, negative, and stable across specifications. Language distance, by contrast, remains negative and statistically significant. These results suggest that the main completion patterns are not driven by racial heterogeneity within either domestic or international students. Instead, the relevant variation appears more closely related to linguistic distance across students in the cohort.

Table 3.15: Summary Statistics of Race/Ethnicity Diversity Measures

| Variable                                            | Observations | Mean  | Std. Dev. | Min   | Max   |
|-----------------------------------------------------|--------------|-------|-----------|-------|-------|
| Domestic race/ethnicity diversity                   | 4,391        | 0.489 | 0.256     | 0.000 | 0.938 |
| International race/ethnicity diversity <sup>a</sup> | 4,102        | 0.393 | 0.306     | 0.000 | 0.927 |

*Notes:* The table reports summary statistics for domestic and international race/ethnicity diversity measured at the cohort level. The number of observations differs across measures because each diversity index is defined only for cohorts with at least one student in the relevant subgroup. Domestic race/ethnicity diversity is undefined for cohorts with no domestic students, and international race/ethnicity diversity is undefined for cohorts with no international students.

Table 3.16: Pairwise Correlations Among Race/Ethnicity Diversity and Language Distance Measures

|                                        | Domestic<br>Race/Ethnicity<br>Diversity | International<br>Race/Ethnicity<br>Diversity | Language<br>Distance |
|----------------------------------------|-----------------------------------------|----------------------------------------------|----------------------|
| Domestic race/ethnicity diversity      | 1.000                                   |                                              |                      |
| International race/ethnicity diversity | -0.016                                  | 1.000                                        |                      |
| Language distance                      | -0.122*                                 | 0.220*                                       | 1.000                |

*Notes:* The table reports pairwise correlations among domestic race/ethnicity diversity, international race/ethnicity diversity, and language distance. \* $p < 0.05$ .

Table 3.17: Effects of Race/Ethnicity Diversity Measures on 7-Year Ph.D. Completion

| Parameter        | Variable                               | 7-Year Ph.D. Completion    |                                 |                   |
|------------------|----------------------------------------|----------------------------|---------------------------------|-------------------|
|                  |                                        | Domestic<br>Race/Ethnicity | International<br>Race/Ethnicity | Full              |
|                  |                                        | (1)                        | (2)                             | (3)               |
| $\beta_1$        | Gender balance                         | 0.032<br>(0.037)           | 0.032<br>(0.039)                | 0.031<br>(0.039)  |
| $\beta_2$        | Domestic race/ethnicity diversity      | -0.018<br>(0.029)          |                                 | -0.011<br>(0.030) |
| $\beta_3$        | International race/ethnicity diversity |                            | -0.011<br>(0.036)               | -0.008<br>(0.036) |
| Observations     |                                        | 4,391                      | 4,102                           | 4,057             |
| Program clusters |                                        | 56                         | 56                              | 56                |

*Notes:* Estimates are from linear probability models. The dependent variable is an indicator for completing the Ph.D. within seven years. Columns (1) and (2) include domestic race/ethnicity diversity and international race/ethnicity diversity separately; column (3) includes both measures jointly. The number of observations differs across columns because each diversity measure is defined only for cohorts with at least one student in the relevant subgroup; the full specification is estimated on cohorts for which both measures are defined. All specifications include gender balance, cohort size, age, age-squared, international status, female status, race/ethnicity indicators, program fixed effects, and entry-year fixed effects. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

### 3.7.4 Country-of-Origin Diversity and Language Distance

As discussed above, language distance is constructed from the languages associated with students' countries of origin and is therefore mechanically related to the diversity of countries represented in a cohort. This section examines whether the completion results reflect country-of-origin diversity itself or the linguistic separation that arises from differences in students' countries of origin.

Figure 3.7 shows that country-of-origin diversity and language distance are positively related but not identical.<sup>13</sup> The measures differ because country-of-origin diversity treats all cross-country pairs symmetrically, whereas language distance gives more weight to pairs from linguistically distant backgrounds. Thus, a cohort may include students from different countries but add relatively little language distance if those students share similar linguistic backgrounds.

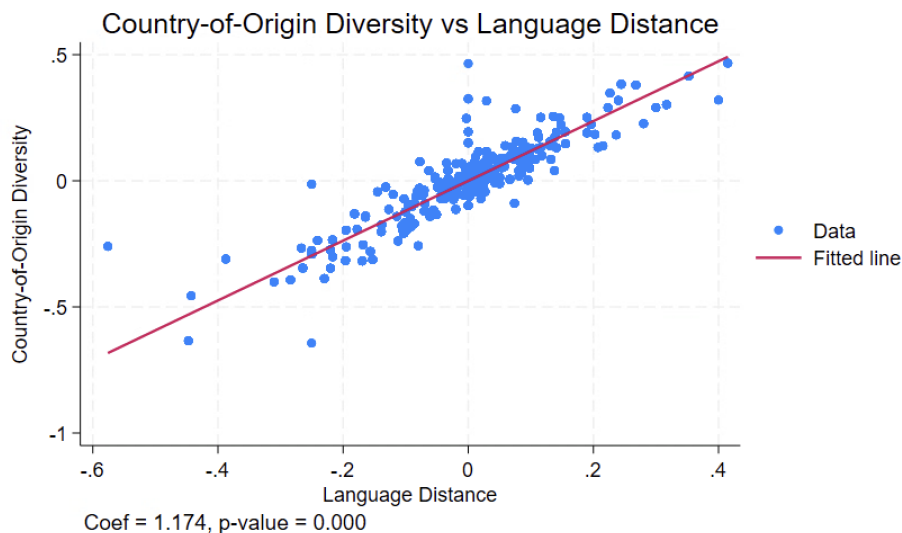


Figure 3.7: Relationship Between Country-of-Origin Diversity and Language Distance

Table 3.18 re-estimates Equation 3.1 after replacing language distance with country-of-origin diversity and then including both measures jointly. Column (1) shows that, unlike language distance in the baseline specification, country-of-origin diversity does not provide clear

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<sup>13</sup>Country-of-origin diversity is measured using a fractionalization index, defined as the probability that two randomly selected students from the same cohort come from different countries.

evidence of a negative association with seven-year Ph.D. completion. In Column (2), which includes both country-of-origin diversity and language distance, the coefficient on country-of-origin diversity becomes positive and remains statistically insignificant, while language distance remains negative and statistically significant. Race/ethnicity diversity also remains negative and statistically significant across both specifications. These results suggest that the number of countries represented in a cohort is not the central margin linking international peer composition to completion. Instead, the relevant variation appears to be the extent of linguistic separation within the cohort.

Table 3.18: Country-of-Origin Diversity, Language Distance, and 7-Year Ph.D. Completion

| Parameter        | Variable                    | 7-Year Ph.D. Completion  |                           |
|------------------|-----------------------------|--------------------------|---------------------------|
|                  |                             | Country Diversity<br>(1) | Full Specification<br>(2) |
| $\beta_1$        | Gender balance              | 0.019<br>(0.037)         | 0.027<br>(0.037)          |
| $\beta_2$        | Race/ethnicity diversity    | -0.113**<br>(0.054)      | -0.124**<br>(0.051)       |
| $\beta_3$        | Country-of-origin diversity | -0.093<br>(0.064)        | 0.120<br>(0.126)          |
| $\beta_4$        | Language distance           |                          | -0.305*<br>(0.165)        |
| Observations     |                             | 4,436                    | 4,436                     |
| Program clusters |                             | 56                       | 56                        |

*Notes:* Estimates are from linear probability models. The dependent variable is an indicator for completing the Ph.D. within seven years. Column (1) replaces language distance with country-of-origin diversity. Column (2) includes both country-of-origin diversity and language distance. All specifications follow Equation 3.1 and include the same individual-level controls, cohort size, program fixed effects, and entry-year fixed effects as the baseline model. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

### 3.7.5 Robustness to Minimum Cohort Size

The main analysis restricts the sample to cohorts with at least eight entering students. This restriction reduces noise in cohort-composition measures, but it may raise concern that the results depend on a particular cutoff. Table 3.19 addresses this concern by re-estimating the full specification using alternative minimum cohort-size thresholds.

The results are broadly stable across cutoffs. As the minimum cohort size increases, the number of observations and clusters declines, but the coefficients on race/ethnicity diversity and language distance remain consistently negative and similar in magnitude to the baseline estimates. Race/ethnicity diversity is statistically significant in most specifications, and language distance becomes statistically significant under more restrictive cohort-size thresholds. Gender balance remains small and statistically insignificant throughout.

Overall, the robustness checks support the main interpretation. The relationship between cohort composition and doctoral completion is not explained by simple demographic shares, by racial heterogeneity within only domestic or international students, by country-of-origin diversity alone, or by the specific cohort-size restriction used in the baseline sample. The evidence instead points to dimensions of cohort structure, especially racial diversity and linguistic distance, as the margins most closely associated with doctoral progress.

Table 3.19: Robustness of Diversity Effects by Minimum Cohort Size

| Parameter        | Variable                 | 7-Year Ph.D. Completion |                     |                     |                     |                      |
|------------------|--------------------------|-------------------------|---------------------|---------------------|---------------------|----------------------|
|                  |                          | 6 or<br>more<br>(1)     | 7 or<br>more<br>(2) | 8 or<br>more<br>(3) | 9 or<br>more<br>(4) | 10 or<br>more<br>(5) |
| $\beta_1$        | Gender balance           | -0.011<br>(0.029)       | -0.019<br>(0.034)   | -0.025<br>(0.037)   | -0.020<br>(0.044)   | -0.029<br>(0.053)    |
| $\beta_2$        | Race/ethnicity diversity | -0.095**<br>(0.044)     | -0.109**<br>(0.049) | -0.110*<br>(0.056)  | -0.128**<br>(0.060) | -0.103<br>(0.068)    |
| $\beta_3$        | Language distance        | -0.057<br>(0.064)       | -0.084<br>(0.078)   | -0.169**<br>(0.083) | -0.149*<br>(0.086)  | -0.227**<br>(0.088)  |
| Observations     |                          | 5,679                   | 4,979               | 4,436               | 3,997               | 3,410                |
| Program clusters |                          | 93                      | 70                  | 56                  | 46                  | 34                   |

*Notes:* Estimates are from linear probability models. The dependent variable is an indicator for completing the Ph.D. within seven years. Each column restricts the sample to program-by-entry-year cohorts with at least the indicated number of students. Column (3), which restricts the sample to cohorts with at least eight students, corresponds to the main analytic sample. All specifications include cohort size, age, age-squared, international status, female status, race/ethnicity indicators, program fixed effects, and entry-year fixed effects. Standard errors are clustered at the program level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

## 3.8 Discussion and Conclusion

This paper examines how the composition of doctoral cohorts shapes academic progress. U.S. doctoral programs have become increasingly diverse along gender, racial/ethnic, and linguistic dimensions, yet most evidence on diversity in higher education comes from undergraduate settings. Doctoral training differs in important ways: students enter small cohorts, interact repeatedly over several years, and rely heavily on informal peer networks for information about coursework, qualifying exams, advisor matching, research opportunities, and professional norms. In this setting, cohort composition may affect outcomes not only by exposing students to different perspectives but also by shaping how easily they form productive academic and social connections.

The results show that cohort diversity matters differently across dimensions of doctoral training environments. Gender balance has no estimated effect on seven-year Ph.D. completion. Racial/ethnic diversity has negative estimated effects on completion in some specifications and appears more consequential for non-White students and students in non-STEM fields. Language distance has the most consistently negative estimated effects, reducing completion rates for both domestic and international students, with stronger effects in STEM programs. These patterns suggest that different forms of diversity operate through different social and institutional channels.

These negative estimates should not be interpreted as evidence against diversity in doctoral education. Instead, the concentration of adverse effects among particular student groups and fields suggests that increasing diversity makes it especially important to identify where vulnerabilities arise and what forms of support are needed. The alternative peer-composition analyses further show that simple increases in the shares of female, non-White, or international students are not negatively related to academic outcomes. Thus, the relevant challenge is not representation itself, but the forms of social, cultural, and linguistic heterogeneity that extend beyond representation. Programs that admit diverse cohorts may therefore need to pair broader representation with targeted support, including language sup-

port, early cohort integration, peer mentoring, advising structures, and opportunities for cross-group collaboration.

The analysis has several limitations. The data come from public universities in one state, and the results may not generalize to institutions with different selectivity, advising systems, or funding structures. Although the models use within-program variation and include program fixed effects, entry-year fixed effects, individual controls, and cohort size, changes in cohort composition may still be correlated with unobserved changes in admissions, funding, faculty availability, student preparation, or departmental climate. The data also do not observe the peer interactions through which cohort composition may affect outcomes, such as study groups, advising relationships, mentoring quality, friendship networks, or language proficiency. Future research combining administrative, survey, network, and qualitative data could clarify these mechanisms. Overall, the findings suggest that diversity in doctoral education is not only about who enters a program, but also about whether students can communicate, collaborate, and build academic support networks after they arrive.

# Bibliography

- M. Abegaz, S. Lahiri, and A. K. M. M. Morshed. Does the presence of international students improve domestic graduations in the U.S.? *The Quarterly Review of Economics and Finance*, 75:95–108, 2020. URL <https://doi.org/10.1016/j.qref.2019.05.008>.
- A. Alesina and E. La Ferrara. Ethnic diversity and economic performance. *Journal of Economic Literature*, 43(3):762–800, 2005. URL <https://doi.org/10.1257/002205105774431243>.
- J. G. Altonji, E. Blom, and C. Meghir. Heterogeneity in human capital investments: High school curriculum, college major, and careers. *Annual Review of Economics*, 4:185–223, 2012.
- J. G. Altonji, P. Arcidiacono, and A. Maurel. The analysis of field choice in college and graduate school: Determinants and wage effects. In E. A. Hanushek, S. Machin, and L. Woessmann, editors, *Handbook of the Economics of Education*, volume 5, pages 305–396. Elsevier, 2016.
- M. Anelli, K. Shih, and K. Williams. Foreign students in college and the supply of STEM graduates. *Journal of Labor Economics*, 41(2):511–563, 2023. URL <https://doi.org/10.1086/719964>.
- A. L. Antonio, M. J. Chang, K. Hakuta, D. A. Kenny, S. Levin, and J. F. Milem. Effects of racial diversity on complex thinking in college students. *Psychological Science*, 15(8):507–510, 2004. URL <https://doi.org/10.1111/j.0956-7976.2004.00710.x>.
- P. Arcidiacono. Ability sorting and the returns to college major. *Journal of Econometrics*, 121(1–2):343–375, 2004.

- D. A. Black, A. M. Haviland, S. G. Sanders, and L. J. Taylor. Gender wage disparities among the highly educated. *Journal of Human Resources*, 43(3):630–659, 2008.
- Z. Bleemer. Affirmative action, mismatch, and economic mobility after california’s proposition 209. *The Quarterly Journal of Economics*, 137(1):115–160, 2022. URL <https://doi.org/10.1093/qje/qjab027>.
- G. J. Borjas. Do foreign students crowd out native students from graduate programs? Technical Report 12094, National Bureau of Economic Research, 2007.
- V. K. Bostwick and B. A. Weinberg. Peer effects in doctoral education: Evidence from female students in STEM programs. *Labour Economics*, 78:102210, 2022. URL <https://doi.org/10.1016/j.labeco.2022.102210>.
- J. Bound, S. Turner, and P. Walsh. Internationalization of U.S. doctorate education. In R. B. Freeman and D. L. Goroff, editors, *Science and Engineering Careers in the United States: An Analysis of Markets and Employment*, pages 59–98. University of Chicago Press, Chicago, IL, 2009. URL <https://doi.org/10.7208/chicago/9780226261904.003.0003>.
- J. Bound, B. Braga, G. Khanna, and S. Turner. The globalization of postsecondary education: The role of international students in the U.S. higher education system. *Journal of Economic Perspectives*, 35(1):163–184, 2021. URL <https://doi.org/10.1257/jep.35.1.163>.
- N. A. Bowman. College diversity experiences and cognitive development: A meta-analysis. *Review of Educational Research*, 80(1):4–33, 2010. URL <https://doi.org/10.3102/0034654309352495>.
- C. Brown and M. Corcoran. Sex-based differences in school content and the male-female wage gap. *Journal of Labor Economics*, 15(3):431–465, 1997.
- K. F. Butcher, P. J. McEwan, and A. Weerapana. Women’s colleges and economics major

- choice: Evidence from wellesley college applicants. *Feminist Economics*, 30(2):123–161, 2024. URL <https://doi.org/10.1080/13545701.2024.2334886>.
- A. Calkins, A. J. Binder, D. Shaat, and B. Timpe. When sarah meets lawrence: The effects of coeducation on women’s college major choices. *American Economic Journal: Applied Economics*, 15(3):1–34, 2023. URL <https://doi.org/10.1257/app.20210692>.
- H. Cassidy and A. Gaulke. The increasing penalty to occupation-education mismatch. *Economic Inquiry*, 62(2):607–632, 2024.
- A. Chevalier, I. E. Isphording, and E. Lisauskaite. Peer diversity, college performance and educational choices. *Labour Economics*, 64:101833, 2020. URL <https://doi.org/10.1016/j.labeco.2020.101833>.
- P. R. Clance and S. A. Imes. The imposter phenomenon in high achieving women: Dynamics and therapeutic intervention. *Psychotherapy: Theory, Research & Practice*, 15(3):241–247, 1978. URL <https://doi.org/10.1037/h0086006>.
- N. Dasgupta, M. M. Scircle, and M. Hunsinger. Female peers in small work groups enhance women’s motivation, verbal participation, and career aspirations in engineering. *Proceedings of the National Academy of Sciences*, 112(16):4988–4993, 2015. URL <https://doi.org/10.1073/pnas.1422822112>.
- A. F. Del Rossi and J. Hersch. Double your major, double your return? *Economics of Education Review*, 27(4):375–386, 2008.
- A. F. Del Rossi and J. Hersch. The private and social benefits of double majors. *Journal of Benefit-Cost Analysis*, 7(2):292–325, 2016.
- A. K. Dills. Classroom diversity and academic outcomes. *Economic Inquiry*, 56(1):304–316, 2018. URL <https://doi.org/10.1111/ecin.12481>.
- D. Eppele and R. E. Romano. Peer effects in education: A survey of the theory and evidence. In J. Benhabib, A. Bisin, and M. O. Jackson, editors, *Handbook of Social Economics*,

- volume 1B, pages 1053–1163. North-Holland, 2011. URL <https://doi.org/10.1016/B978-0-444-53707-2.00003-7>.
- R. W. Fairlie, G. Millhauser, D. Oliver, and R. Roland. The effects of male peers on the educational outcomes of female college students in STEM: Experimental evidence from partnerships in chemistry courses. *PLOS ONE*, 15(7):e0235383, 2020. URL <https://doi.org/10.1371/journal.pone.0235383>.
- E. M. Flores-Scott and M. Nerad. Peers in doctoral education: Unrecognized learning partners. *New Directions for Higher Education*, 2012(157):73–83, 2012. URL <https://doi.org/10.1002/he.20007>.
- S. K. Gardner. “i heard it through the grapevine”: Doctoral student socialization in chemistry and history. *Higher Education*, 54(5):723–740, 2007. URL <https://doi.org/10.1007/s10734-006-9020-x>.
- C. M. Golde. The role of the department and discipline in doctoral student attrition: Lessons from four departments. *The Journal of Higher Education*, 76(6):669–700, 2005. URL <https://doi.org/10.1080/00221546.2005.11772304>.
- A. L. Griffith and J. B. Main. First impressions in the classroom: How do class characteristics affect student grades and majors? *Economics of Education Review*, 69:125–137, 2019. URL <https://doi.org/10.1016/j.econedurev.2019.02.001>.
- J. Grogger and E. Eide. Changes in college skills and the rise in the college wage premium. *Journal of Human Resources*, 30(2):280–310, 1995.
- T. Gurevich, P. R. Herman, F. Toubal, and Y. V. Yotov. The domestic and international common language (DICL) database. Economics Working Paper 2024–03–A, U.S. International Trade Commission, 2024.
- P. Gurin, E. L. Dey, S. Hurtado, and G. Gurin. Diversity and higher education: Theory and impact on educational outcomes. *Harvard Educational Review*, 72(3):330–367, 2002. URL <https://doi.org/10.17763/haer.72.3.01151786u134n051>.

- A. S. Hanks et al. Do double majors face less risk? an analysis of human capital diversification. Technical Report 32095, National Bureau of Economic Research, 2024.
- S. W. Hemelt. The college double major and subsequent earnings. *Education Economics*, 18(2):167–189, 2010.
- C. M. Hoxby. Peer effects in the classroom. Technical Report 7867, National Bureau of Economic Research, 2000.
- S. Jiang. *Essays on College Major, College Curriculum, and Subsequent Labor Market Outcomes*. Doctoral dissertation, The Ohio State University, 2019. URL [http://rave.ohiolink.edu/etdc/view?acc\\_num=osu1545831469436781](http://rave.ohiolink.edu/etdc/view?acc_num=osu1545831469436781).
- R. M. Kanter. Some effects of proportions on group life: Skewed sex ratios and responses to token women. *American Journal of Sociology*, 82(5):965–990, 1977. URL <https://doi.org/10.1086/226425>.
- L. J. Kirkeboen, E. Leuven, and M. Mogstad. Field of study, earnings, and self-selection. *Quarterly Journal of Economics*, 131(3):1057–1111, 2016.
- Y.-H. Kuo. Language challenges faced by international graduate students in the united states. *Journal of International Students*, 1(2):38–42, 2011. URL <https://doi.org/10.32674/jis.v1i2.551>.
- Y. Lau. Does racial diversity improve academic outcomes? a natural experiment in higher education classrooms. *Labour Economics*, 78:102254, 2022. URL <https://doi.org/10.1016/j.labeco.2022.102254>.
- V. Lavy and A. Schlosser. Gender peer effects at school. *American Economic Journal: Applied Economics*, 3(2):1–33, 2011.
- E. P. Lazear. Globalisation and the market for team-mates. *The Economic Journal*, 109(454):C15–C40, 1999. URL <https://doi.org/10.1111/1468-0297.00414>.

- J. Luo and D. Jamieson-Drake. Examining the educational benefits of interacting with international students. *Journal of International Students*, 3(2):85–101, 2013.
- S. Luo. Peer effects of international students in U.S. higher education. EdWorkingPaper 25–1207, Annenberg Institute at Brown University, 2025. URL <https://doi.org/10.26300/qh8c-q769>.
- M. A. Maher, A. M. Wofford, J. Roksa, and D. F. Feldon. Exploring early exits: Doctoral attrition in the biomedical sciences. *Journal of College Student Retention: Research, Theory & Practice*, 22(2):205–226, 2020. URL <https://doi.org/10.1177/1521025117736871>.
- D. Mitra, P. N. Golder, and M. Topchy. Racial diversity in higher education is associated with higher student salaries. *Nature*, 2026. URL <https://doi.org/10.1038/s41586-026-10425-7>.
- National Academies of Sciences, Engineering, and Medicine. *Graduate STEM Education for the 21st Century*. The National Academies Press, Washington, DC, 2018. URL <https://doi.org/10.17226/25038>.
- National Center for Science and Engineering Statistics. Doctorate recipients from U.S. universities: 2024 data tables. NSF 25-349, National Science Foundation, 2025a. URL <https://ncses.nsf.gov/pubs/nsf25349>.
- National Center for Science and Engineering Statistics. Women, minorities, and persons with disabilities in science and engineering. Alexandria, VA: National Science Foundation, 2025b. URL <https://ncses.nsf.gov/pubs/nsf25336>.
- National Institutes of Health. NIH grants policy statement: Ruth l. kirschstein national research service awards, section 11.2.2 eligibility, 2026. URL [https://grants.nih.gov/grants/policy/nihgps/html5/section\\_11/11.2.2\\_eligibility.htm](https://grants.nih.gov/grants/policy/nihgps/html5/section_11/11.2.2_eligibility.htm).
- National Science Foundation. Graduate research fellowship program (GRFP): NSF 25-547,

2025. URL <https://www.nsf.gov/funding/opportunities/grfp-nsf-graduate-research-fellowship-program/nsf25-547/solicitation>.
- P. E. Oliver, G. Marwell, and R. Teixeira. A theory of the critical mass. i. interdependence, group heterogeneity, and the production of collective action. *American Journal of Sociology*, 91(3):522–556, 1985. URL <https://doi.org/10.1086/228313>.
- H. Oosterbeek and R. J. G. van Ewijk. Gender peer effects in university: Evidence from a randomized experiment. *Economics of Education Review*, 38:51–63, 2014. URL <https://doi.org/10.1016/j.econedurev.2013.11.002>.
- H. Orlans. Affirmative action in higher education. *The Annals of the American Academy of Political and Social Science*, 523(1):144–158, 1992. URL <https://doi.org/10.1177/0002716292523001013>.
- R. N. Pitt and S. A. Tepper. Double majors: Influences, identities, and impacts. Prepared for the Teagle Foundation, Curb Center, Vanderbilt University, 2012.
- J. R. Posselt. Normalizing struggle: Dimensions of faculty support for doctoral students and implications for persistence and well-being. *The Journal of Higher Education*, 89(6): 988–1013, 2018. URL <https://doi.org/10.1080/00221546.2018.1449080>.
- M. C. Regets. International migration of highly skilled workers. Technical Report SRS 07–203, National Science Foundation, 2007.
- J. Robst. Education and job match: The relatedness of college major and work. *Economics of Education Review*, 26(4):397–407, 2007.
- B. Sacerdote. Peer effects in education: How might they work, how big are they and how much do we know thus far? In E. A. Hanushek, S. Machin, and L. Woessmann, editors, *Handbook of the Economics of Education*, volume 3, pages 249–277. North-Holland, 2011. URL <https://doi.org/10.1016/B978-0-444-53429-3.00004-1>.

- K. Shih. Do international students crowd-out or cross-subsidize americans in higher education? *Journal of Public Economics*, 156:170–184, 2017. URL <https://doi.org/10.1016/j.jpubeco.2017.10.003>.
- K. Singhal and E. Sierminska. Who studies what? country of origin, gender, and field specialization among economics PhDs. IZA Discussion Paper 18348, IZA Institute of Labor Economics, 2025. URL <https://docs.iza.org/dp18348.pdf>.
- C. M. Sloane, E. G. Hurst, and D. A. Black. College majors, occupations, and the gender wage gap. *Journal of Economic Perspectives*, 35(4):223–248, 2021.
- H. Tenzer, M. Pudelko, and A.-W. Harzing. The impact of language barriers on trust formation in multinational teams. *Journal of International Business Studies*, 45(5):508–535, 2014. URL <https://doi.org/10.1057/jibs.2013.64>.
- M. Thompson and D. Sekaquaptewa. When being different is detrimental: Solo status and the performance of women and racial minorities. *Analyses of Social Issues and Public Policy*, 2(1):183–203, 2002. URL <https://doi.org/10.1111/j.1530-2415.2002.00037.x>.
- M. J. Uddin and R. Tout. The impact of dual majors on income based on the american community survey, 2020. Unpublished manuscript.
- P. T. von Hippel and B. A. Schuetze. Heterogeneity of treatment effects. Working paper, Annenberg Institute, 2025.
- C. Wendler, B. Bridgeman, R. Markle, F. Cline, N. E. Bell, P. H. McAllister, and J. Kent. Pathways through graduate school and into careers. Technical report, Educational Testing Service and Council of Graduate Schools, 2012.
- D. J. Wu, K. C. Thiem, and N. Dasgupta. Female peer mentors early in college have lasting positive impacts on female engineering students that persist beyond graduation. *Nature Communications*, 13:6837, 2022. URL <https://doi.org/10.1038/s41467-022-34508-x>.

- B. Zafar. Double majors: One for me, one for the parents? *Economic Inquiry*, 50(2):287–308, 2012.
- B. Zafar. College major choice and the gender gap. *Journal of Human Resources*, 48(3): 545–595, 2013.
- L. Zhang. Do foreign doctorate recipients displace U.S. doctorate recipients at U.S. universities? pages 209–223. Cornell University Press, Ithaca, NY. URL <https://www.jstor.org/stable/10.7591/j.ctt7z914.18>.
- Q. Zhu and L. Zhang. Effects of a double major on post-baccalaureate outcomes. *Education Finance and Policy*, 16(1):146–169, 2021.
- U. Zölitz and J. Feld. The effect of peer gender on major choice in business school. *Management Science*, 67(11):6963–6979, 2021. URL <https://doi.org/10.1287/mnsc.2020.3860>.

# Appendix A

## Additional Tables and Figures

### A.1 Proportion of Students with Double Majors by Cohort

### A.2 Heterogeneity Within Broad Fields

#### A.2.1 Comparison with High- and Low-Return Benchmarks

### A.3 Estimated Probability of Graduate Degree Attainment by Double-Major Combination and Gender

### A.4 Heterogeneity by Age

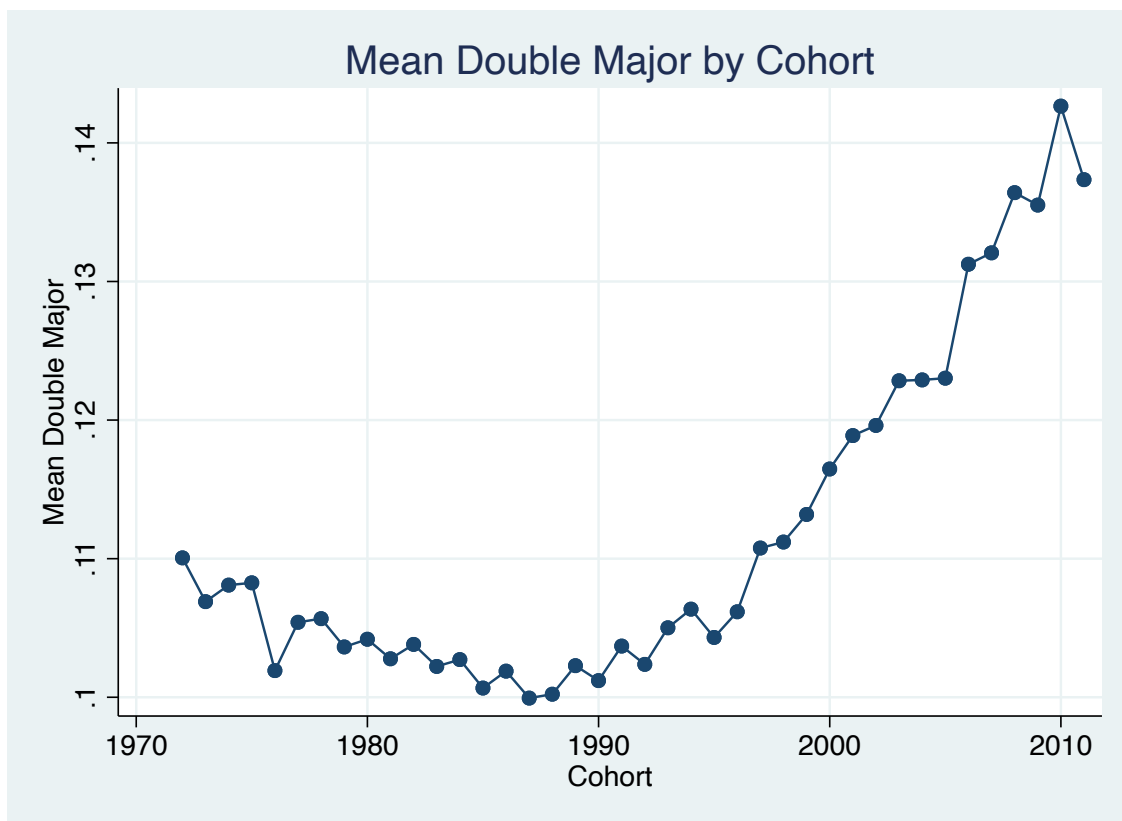


Figure A.1: Proportion of Students with Double Majors by Cohort

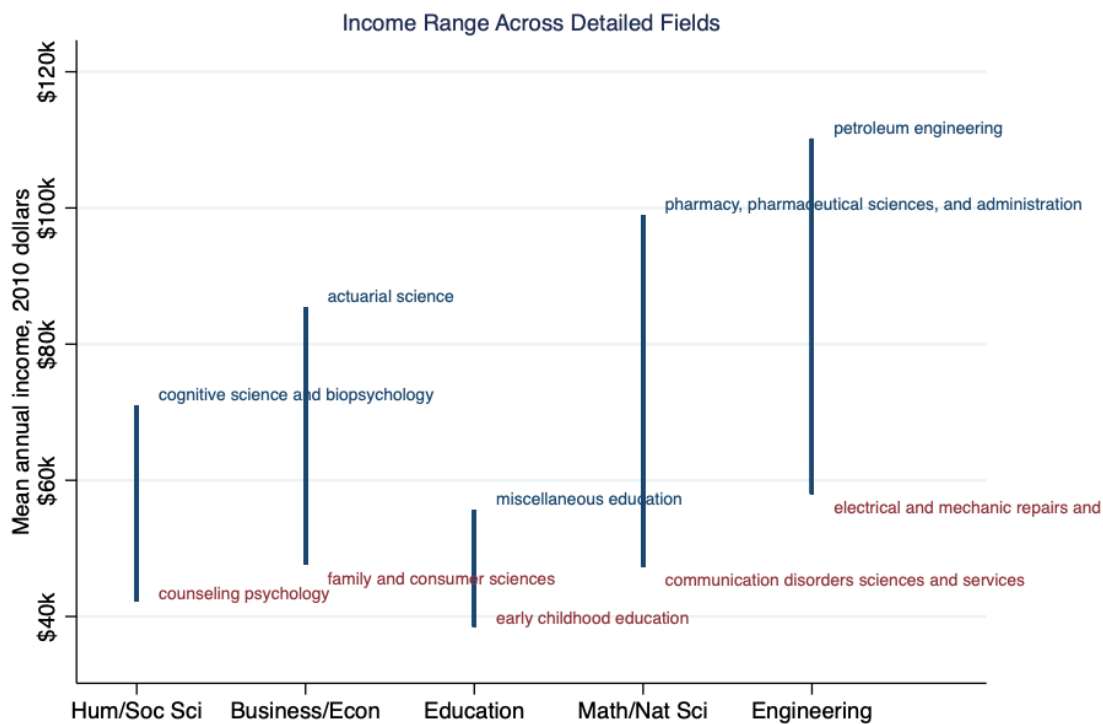


Figure A.2: Income Dispersion Across Detailed Fields

*Notes:* Each vertical line shows the range of mean annual income across detailed first fields within a broad field category. Labels identify the highest- and lowest-income detailed fields in each category. Income is deflated to 2010 dollars. The figure illustrates that broad field categories contain substantial within-category variation in earnings.

Table A.1: Classification of ACS Detailed Field-of-Degree Codes: Arts, Business, and Education

| Group            | ACS/IPUMS detailed field-of-degree codes and labels                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               |
|------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Arts</b>      | 1501: Area, Ethnic, and Civilization Studies; 1900: Communications; 1901: Communications; 1902: Journalism; 1903: Mass Media; 2201: Cosmetology Services and Culinary Arts; 2600: Linguistics and Foreign Languages; 2601: Linguistics and Comparative Language and Literature; 2602: French, German, Latin and Other Common Foreign Language Studies; 2603: Other Foreign Languages; 2901: Family and Consumer Sciences; 3200: Law; 3201: Court Reporting; 3202: Pre-Law and Legal Studies; 3300: English Language, Literature, and Composition; 3301: English Language and Literature; 3302: Composition and Speech; 3400: Liberal Arts and Humanities; 3401: Liberal Arts; 3402: Humanities; 3501: Library Science; 4001: Intercultural and International Studies; 4101: Physical Fitness, Parks, Recreation, and Leisure; 4801: Philosophy and Religious Studies; 4901: Theology and Religious Vocations; 5200: Psychology; 5201: Educational Psychology; 5202: Clinical Psychology; 5203: Counseling Psychology; 5205: Industrial and Organizational Psychology; 5206: Social Psychology; 5299: Miscellaneous Psychology; 5301: Criminal Justice and Fire Protection; 5400: Public Affairs, Policy, and Social Work; 5401: Public Administration; 5402: Public Policy; 5403: Human Services and Community Organization; 5404: Social Work; 5500: General Social Sciences; 5502: Anthropology and Archeology; 5503: Criminology; 5504: Geography; 5505: International Relations; 5506: Political Science and Government; 5507: Sociology; 5599: Miscellaneous Social Sciences; 5801: Precision Production and Industrial Arts; 6000: Fine Arts; 6001: Drama and Theater Arts; 6002: Music; 6003: Visual and Performing Arts; 6004: Commercial Art and Graphic Design; 6005: Film, Video and Photographic Arts; 6006: Art History and Criticism; 6007: Studio Arts; 6099: Miscellaneous Fine Arts; 6402: History; 6403: United States History. |
| <b>Business</b>  | 1101: Agriculture Production and Management; 1102: Agricultural Economics; 1904: Advertising and Public Relations; 5501: Economics; 6200: General Business; 6201: Accounting; 6202: Actuarial Science; 6203: Business Management and Administration; 6204: Operations, Logistics and E-Commerce; 6205: Business Economics; 6206: Marketing and Marketing Research; 6207: Finance; 6209: Human Resources and Personnel Management; 6210: International Business; 6211: Hospitality Management; 6212: Management Information Systems and Statistics; 6299: Miscellaneous Business and Medical Administration.                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       |
| <b>Education</b> | 2300: General Education; 2301: Educational Administration and Supervision; 2303: School Student Counseling; 2304: Elementary Education; 2305: Mathematics Teacher Education; 2306: Physical and Health Education Teaching; 2307: Early Childhood Education; 2308: Science and Computer Teacher Education; 2309: Secondary Teacher Education; 2310: Special Needs Education; 2311: Social Science or History Teacher Education; 2312: Teacher Education: Multiple Levels; 2313: Language and Drama Education; 2314: Art and Music Education; 2399: Miscellaneous Education.                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        |

*Notes:* Codes are Census/ACS detailed field-of-degree codes from IPUMS DEGFELD2.

Table A.2: Classification of ACS Detailed Field-of-Degree Codes: Engineering and Math/Science

| Group               | ACS/IPUMS detailed field-of-degree codes and labels                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   |
|---------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Engineering</b>  | 1401: Architecture; 2001: Communication Technologies; 2100: Computer and Information Systems; 2101: Computer Programming and Data Processing; 2102: Computer Science; 2105: Information Sciences; 2106: Computer Information Management and Security; 2107: Computer Networking and Telecommunications; 2400: General Engineering; 2401: Aerospace Engineering; 2402: Biological Engineering; 2403: Architectural Engineering; 2404: Biomedical Engineering; 2405: Chemical Engineering; 2406: Civil Engineering; 2407: Computer Engineering; 2408: Electrical Engineering; 2409: Engineering Mechanics, Physics, and Science; 2410: Environmental Engineering; 2411: Geological and Geophysical Engineering; 2412: Industrial and Manufacturing Engineering; 2413: Materials Engineering and Materials Science; 2414: Mechanical Engineering; 2415: Metallurgical Engineering; 2416: Mining and Mineral Engineering; 2417: Naval Architecture and Marine Engineering; 2418: Nuclear Engineering; 2419: Petroleum Engineering; 2499: Miscellaneous Engineering; 2500: Engineering Technologies; 2501: Engineering and Industrial Management; 2502: Electrical Engineering Technology; 2503: Industrial Production Technologies; 2504: Mechanical Engineering Related Technologies; 2599: Miscellaneous Engineering Technologies; 3801: Military Technologies; 5601: Construction Services; 5701: Electrical and Mechanic Repairs and Technologies; 5901: Transportation Sciences and Technologies.                                                                                                                                                                                                                                                    |
| <b>Math/Science</b> | 1100: General Agriculture; 1103: Animal Sciences; 1104: Food Science; 1105: Plant Science and Agronomy; 1106: Soil Science; 1199: Miscellaneous Agriculture; 1300: Environment and Natural Resources; 1301: Environmental Science; 1302: Forestry; 1303: Natural Resources Management; 3600: Biology; 3601: Biochemical Sciences; 3602: Botany; 3603: Molecular Biology; 3604: Ecology; 3605: Genetics; 3606: Microbiology; 3607: Pharmacology; 3608: Physiology; 3609: Zoology; 3611: Neuroscience; 3699: Miscellaneous Biology; 3700: Mathematics; 3701: Applied Mathematics; 3702: Statistics and Decision Science; 4000: Interdisciplinary and Multi-Disciplinary Studies (General); 4002: Nutrition Sciences; 4003: Neuroscience; 4005: Mathematics and Computer Science; 4006: Cognitive Science and Biopsychology; 4007: Interdisciplinary Social Sciences; 4008: Multi-disciplinary or General Science; 5000: Physical Sciences; 5001: Astronomy and Astrophysics; 5002: Atmospheric Sciences and Meteorology; 5003: Chemistry; 5004: Geology and Earth Science; 5005: Geosciences; 5006: Oceanography; 5007: Physics; 5008: Materials Science; 5098: Multi-disciplinary or General Science; 5102: Nuclear, Industrial Radiology, and Biological Technologies; 6100: General Medical and Health Services; 6102: Communication Disorders Sciences and Services; 6103: Health and Medical Administrative Services; 6104: Medical Assisting Services; 6105: Medical Technologies Technicians; 6106: Health and Medical Preparatory Programs; 6107: Nursing; 6108: Pharmacy, Pharmaceutical Sciences, and Administration; 6109: Treatment Therapy Professions; 6110: Community and Public Health; 6199: Miscellaneous Health Medical Professions. |

*Notes:* Codes are Census/ACS detailed field-of-degree codes from IPUMS DEGFIEL2.

Table A.3: Double-Major Wages/Earnings Effects Relative to High- and Low-Income Benchmarks

| Benchmark         | Our results         | Uddin and Tout (2020)         | Zhu and Zhang (2021) |                    |
|-------------------|---------------------|-------------------------------|----------------------|--------------------|
|                   | Ages 30–60          | Ages 25–59                    | 1 year after BA      | 4 years after BA   |
| High-income major | −0.009*<br>(0.005)  | −0.047***<br>( $t = -12.33$ ) | −0.074**<br>(0.032)  | 0.041<br>(0.040)   |
| Low-income major  | 0.026***<br>(0.004) | 0.076***<br>( $t = 19.53$ )   | 0.025<br>(0.034)     | 0.097**<br>(0.039) |

*Notes:* The “Our results” column reproduces the full-sample estimates from the main text results, Panel B. We use Engineering as the high-income benchmark and Education as the low-income benchmark because they are the highest- and lowest-paying first-field groups, respectively, in our ACS sample. Estimates from Uddin and Tout (2020) are taken from Table 2, columns (3)–(4), and estimates from Zhu and Zhang (2021) are taken from Table 3, propensity-score-weighted specifications. Coefficients are rounded to three decimal places. For our estimates, standard errors are reported below the coefficients. Uddin and Tout (2020) report  $t$  statistics below the coefficients. Zhu and Zhang (2021) report bootstrapped standard errors clustered at the institutional level below the coefficients. Significance levels follow each original table: for our estimates and Zhu and Zhang (2021),  $*p < 0.10$ ,  $**p < 0.05$ , and  $***p < 0.01$ ; for Uddin and Tout (2020),  $*p < 0.05$ ,  $**p < 0.01$ , and  $***p < 0.001$ .

Table A.4: Double Majors and Post-Baccalaureate Degree Attainment: Female Sample

| Parameter                                                           | First Field                  | Highest Degree      |                     |                      |
|---------------------------------------------------------------------|------------------------------|---------------------|---------------------|----------------------|
|                                                                     |                              | Master's<br>(1)     | Professional<br>(2) | Doctoral<br>(3)      |
| <i>Panel A. Global double-major associations within first field</i> |                              |                     |                     |                      |
| $\beta_2$                                                           | Humanities & Social Sciences | 0.028***<br>(0.004) | -0.002<br>(0.002)   | -0.001<br>(0.002)    |
| $\beta_2 + \beta_{32}$                                              | Business & Economics         | 0.063***<br>(0.005) | 0.028***<br>(0.003) | 0.013***<br>(0.002)  |
| $\beta_2 + \beta_{33}$                                              | Education                    | -0.012<br>(0.008)   | 0.012***<br>(0.003) | 0.009***<br>(0.003)  |
| $\beta_2 + \beta_{34}$                                              | Engineering                  | -0.022**<br>(0.009) | 0.007*<br>(0.004)   | -0.003<br>(0.003)    |
| $\beta_2 + \beta_{35}$                                              | Math & Natural Sciences      | 0.059***<br>(0.006) | 0.011***<br>(0.003) | -0.004<br>(0.003)    |
| <i>Panel B. Local double-major associations within first field</i>  |                              |                     |                     |                      |
| $\beta_2 + \beta_4$                                                 | Humanities & Social Sciences | 0.034***<br>(0.003) | 0.036***<br>(0.002) | 0.014***<br>(0.001)  |
| $\beta_2 + \beta_{32} + \beta_4 + \beta_{52}$                       | Business & Economics         | 0.006<br>(0.004)    | 0.002<br>(0.002)    | -0.003***<br>(0.001) |
| $\beta_2 + \beta_{33} + \beta_4 + \beta_{53}$                       | Education                    | 0.088***<br>(0.007) | 0.011***<br>(0.003) | 0.004*<br>(0.002)    |
| $\beta_2 + \beta_{34} + \beta_4 + \beta_{54}$                       | Engineering                  | 0.033**<br>(0.016)  | 0.005<br>(0.007)    | 0.006<br>(0.006)     |
| $\beta_2 + \beta_{35} + \beta_4 + \beta_{55}$                       | Math & Natural Sciences      | 0.012**<br>(0.005)  | 0.044***<br>(0.004) | 0.031***<br>(0.003)  |
| Observations                                                        |                              | 1,109,462           | 1,109,462           | 1,109,462            |

*Notes:* The dependent variables are indicators for whether the respondent's highest degree is a master's, professional, or doctoral degree. The sample is restricted to women. Panel A reports estimated associations between global double majoring and each type of post-baccalaureate degree within first-field categories. Panel B reports the corresponding associations for local double majoring. All specifications include individual controls, the state unemployment rate, graduation cohort fixed effects, and state fixed effects. Standard errors are clustered by graduation cohort and current state. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

Table A.5: Double Majors and Post-Baccalaureate Degree Attainment: Male Sample

| Parameter                                                           | First Field                  | Highest Degree       |                      |                      |
|---------------------------------------------------------------------|------------------------------|----------------------|----------------------|----------------------|
|                                                                     |                              | Master's<br>(1)      | Professional<br>(2)  | Doctoral<br>(3)      |
| <i>Panel A. Global double-major associations within first field</i> |                              |                      |                      |                      |
| $\beta_2$                                                           | Humanities & Social Sciences | 0.028***<br>(0.004)  | 0.004<br>(0.003)     | 0.001<br>(0.002)     |
| $\beta_2 + \beta_{32}$                                              | Business & Economics         | 0.063***<br>(0.005)  | 0.037***<br>(0.003)  | 0.019***<br>(0.002)  |
| $\beta_2 + \beta_{33}$                                              | Education                    | -0.036***<br>(0.012) | 0.007<br>(0.005)     | 0.006<br>(0.004)     |
| $\beta_2 + \beta_{34}$                                              | Engineering                  | 0.014**<br>(0.005)   | 0.011***<br>(0.002)  | 0.013***<br>(0.002)  |
| $\beta_2 + \beta_{35}$                                              | Math & Natural Sciences      | 0.058***<br>(0.005)  | -0.037***<br>(0.003) | -0.030***<br>(0.003) |
| <i>Panel B. Local double-major associations within first field</i>  |                              |                      |                      |                      |
| $\beta_2 + \beta_4$                                                 | Humanities & Social Sciences | 0.048***<br>(0.003)  | 0.045***<br>(0.002)  | 0.019***<br>(0.002)  |
| $\beta_2 + \beta_{32} + \beta_4 + \beta_{52}$                       | Business & Economics         | 0.022***<br>(0.004)  | 0.006***<br>(0.002)  | -0.001<br>(0.001)    |
| $\beta_2 + \beta_{33} + \beta_4 + \beta_{53}$                       | Education                    | 0.066***<br>(0.013)  | 0.014**<br>(0.006)   | 0.010**<br>(0.005)   |
| $\beta_2 + \beta_{34} + \beta_4 + \beta_{54}$                       | Engineering                  | 0.032***<br>(0.007)  | 0.001<br>(0.002)     | 0.016***<br>(0.003)  |
| $\beta_2 + \beta_{35} + \beta_4 + \beta_{55}$                       | Math & Natural Sciences      | 0.008<br>(0.005)     | 0.011***<br>(0.004)  | 0.046***<br>(0.004)  |
| Observations                                                        |                              | 1,169,232            | 1,169,232            | 1,169,232            |

*Notes:* The dependent variables are indicators for whether the respondent's highest degree is a master's, professional, or doctoral degree. The sample is restricted to men. Panel A reports estimated associations between global double majoring and each type of post-baccalaureate degree within first-field categories. Panel B reports the corresponding associations for local double majoring. All specifications include individual controls, the state unemployment rate, graduation cohort fixed effects, and state fixed effects. Standard errors are clustered by graduation cohort and current state. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

Table A.6: Global and Local Effects of Double Majoring by Age

| Parameter                                                               | First Field                  | Age                  |                      |                      |
|-------------------------------------------------------------------------|------------------------------|----------------------|----------------------|----------------------|
|                                                                         |                              | 30s                  | 40s                  | 50s                  |
|                                                                         |                              | (1)                  | (2)                  | (3)                  |
| <i>Panel A. Global double-major wage differences within first field</i> |                              |                      |                      |                      |
| $\beta_2$                                                               | Humanities & Social Sciences | 0.063***<br>(0.005)  | 0.024***<br>(0.006)  | 0.052***<br>(0.006)  |
| $\beta_2 + \beta_{32}$                                                  | Business & Economics         | 0.016**<br>(0.007)   | -0.012<br>(0.008)    | -0.031***<br>(0.008) |
| $\beta_2 + \beta_{33}$                                                  | Education                    | 0.031***<br>(0.010)  | 0.019<br>(0.012)     | 0.049***<br>(0.010)  |
| $\beta_2 + \beta_{34}$                                                  | Engineering                  | -0.018*<br>(0.010)   | -0.034***<br>(0.011) | -0.067***<br>(0.010) |
| $\beta_2 + \beta_{35}$                                                  | Math & Natural Sciences      | -0.024***<br>(0.007) | -0.032***<br>(0.009) | -0.035***<br>(0.008) |
| <i>Panel B. Local double-major wage differences within first field</i>  |                              |                      |                      |                      |
| $\beta_2 + \beta_4$                                                     | Humanities & Social Sciences | 0.013***<br>(0.004)  | 0.004<br>(0.005)     | 0.002<br>(0.005)     |
| $\beta_2 + \beta_{32} + \beta_4 + \beta_{52}$                           | Business & Economics         | 0.080***<br>(0.006)  | 0.062***<br>(0.006)  | 0.033***<br>(0.006)  |
| $\beta_2 + \beta_{33} + \beta_4 + \beta_{53}$                           | Education                    | 0.020***<br>(0.008)  | 0.013<br>(0.009)     | 0.024***<br>(0.008)  |
| $\beta_2 + \beta_{34} + \beta_4 + \beta_{54}$                           | Engineering                  | 0.051***<br>(0.011)  | 0.036***<br>(0.012)  | 0.015<br>(0.011)     |
| $\beta_2 + \beta_{35} + \beta_4 + \beta_{55}$                           | Math & Natural Sciences      | -0.018***<br>(0.007) | 0.020**<br>(0.008)   | -0.008<br>(0.008)    |
| Observations                                                            |                              | 786,932              | 731,157              | 701,046              |

*Notes:* The dependent variable is log hourly wage. Panel A reports the estimated wage differences associated with global double majoring within each reported first-field category. Panel B reports the estimated wage differences associated with local double majoring within each reported first-field category. All specifications include individual controls, the state unemployment rate, graduation cohort fixed effects, and state fixed effects. Standard errors are clustered by graduation cohort and current state. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

## Appendix B

### Additional Tables and Figures for International Peer Effects

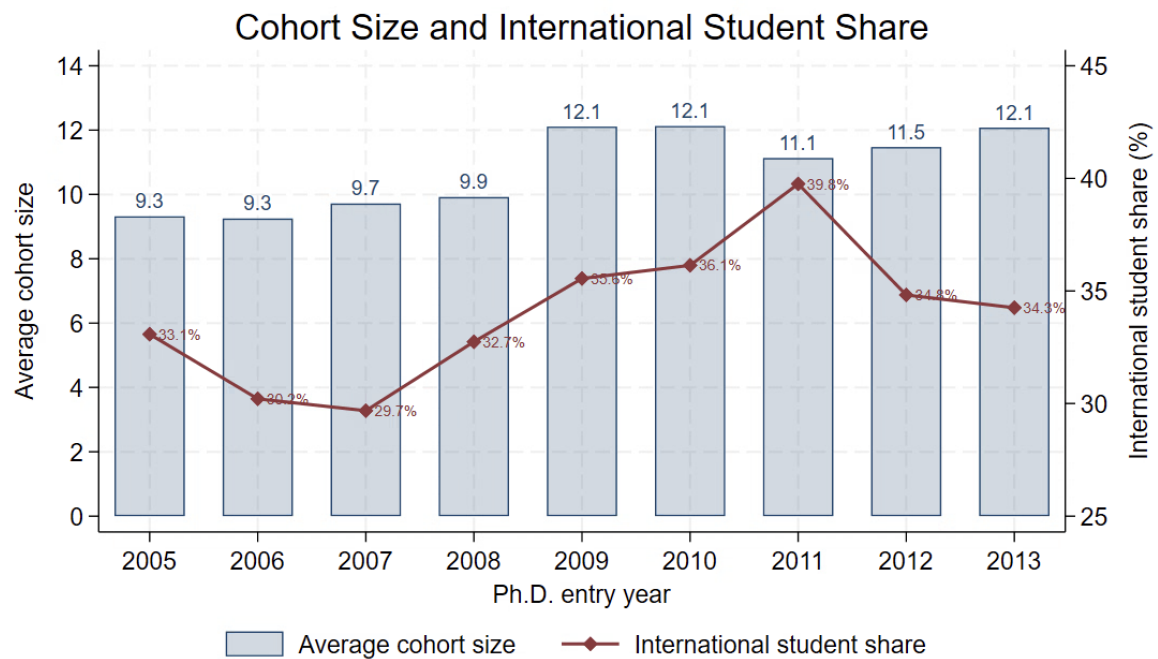


Figure B1: Average Cohort Size and International Student Share by Ph.D. Entry Year

Table B1: Summary Statistics by Field

| No. | Field Title                                      | Cohort Size | Intl. Share | Programs | Cohorts |
|-----|--------------------------------------------------|-------------|-------------|----------|---------|
| 1   | Interdisciplinary Math & Science                 | 6.890       | 0.000       | 1        | 9       |
| 2   | Geography                                        | 6.000       | 0.000       | 1        | 9       |
| 3   | Education, Other                                 | 9.130       | 0.000       | 3        | 25      |
| 4   | Education Administration                         | 9.960       | 0.022       | 2        | 45      |
| 5   | English                                          | 9.190       | 0.025       | 5        | 45      |
| 6   | Psychology                                       | 11.000      | 0.040       | 8        | 55      |
| 7   | Counseling                                       | 6.730       | 0.067       | 3        | 27      |
| 8   | General Health/Public Health                     | 7.820       | 0.104       | 1        | 19      |
| 9   | Veterinary Medicine                              | 9.530       | 0.111       | 1        | 3       |
| 10  | Area, Ethnic, Cultural, and Gender Studies       | 8.940       | 0.111       | 2        | 9       |
| 11  | Education, General                               | 38.190      | 0.167       | 2        | 12      |
| 12  | Music, Performance                               | 15.350      | 0.192       | 2        | 62      |
| 13  | Chemical Engineering                             | 12.020      | 0.250       | 2        | 17      |
| 14  | Specialized Teacher Education                    | 6.910       | 0.250       | 1        | 8       |
| 15  | Protective Services                              | 11.610      | 0.267       | 1        | 9       |
| 16  | Foreign Languages: Romance                       | 11.110      | 0.273       | 3        | 11      |
| 17  | Sociology and Related Social Sciences            | 9.390       | 0.286       | 1        | 9       |
| 18  | Political Science                                | 14.280      | 0.304       | 4        | 23      |
| 19  | Management                                       | 8.340       | 0.324       | 4        | 29      |
| 20  | Civil Engineering                                | 6.500       | 0.333       | 1        | 7       |
| 21  | History                                          | 14.500      | 0.333       | 1        | 6       |
| 22  | Biological and Biomedical Sciences               | 9.100       | 0.355       | 4        | 31      |
| 23  | Linguistics                                      | 6.110       | 0.375       | 1        | 9       |
| 24  | Other Engineering                                | 11.990      | 0.381       | 4        | 23      |
| 25  | Communications                                   | 8.720       | 0.450       | 2        | 18      |
| 26  | Computer Engineering                             | 15.370      | 0.452       | 3        | 22      |
| 27  | Mathematics and Statistics                       | 18.330      | 0.455       | 5        | 29      |
| 28  | Chemistry                                        | 13.480      | 0.489       | 2        | 12      |
| 29  | Forestry, Wildlife, and Natural Resources        | 6.330       | 0.500       | 3        | 6       |
| 30  | Social Work                                      | 7.000       | 0.500       | 1        | 5       |
| 31  | Physics                                          | 12.550      | 0.507       | 5        | 45      |
| 32  | Economics (Social Science)                       | 17.860      | 0.524       | 1        | 9       |
| 33  | Electrical, Electronics, and Communications Eng. | 17.860      | 0.533       | 3        | 9       |
| 34  | Agricultural Science                             | 11.670      | 0.571       | 3        | 9       |
| 35  | Materials Engineering                            | 16.560      | 0.577       | 1        | 9       |
| 36  | Computer Science                                 | 12.000      | 0.589       | 2        | 5       |
| 37  | Mechanical, Industrial, and Manufacturing Eng.   | 15.010      | 0.617       | 2        | 12      |
| 38  | Pharmacy                                         | 12.500      | 0.667       | 1        | 6       |
| 39  | Other Health                                     | 8.200       | 0.750       | 1        | 6       |

Notes: “Cohort Size” is the mean number of entering students per cohort; “Intl. Share” is the average fraction of international students (0–1); “Programs” counts distinct programs (CIP-code and institution); “Cohorts” counts distinct program-year cells in the sample.

# Appendix C

## Additional Tables and Figures for Diversity in Doctoral Programs

### C.1 Country-Level Linguistic Distance from the United States

Table C1: Country-Level Linguistic Distance from the United States

| Country             | Dist. | Country           | Dist. | Country        | Dist. |
|---------------------|-------|-------------------|-------|----------------|-------|
| U.S. Virgin Islands | 0.02  | Palau             | 0.05  | Ireland        | 0.05  |
| Cook Islands        | 0.05  | Dominica          | 0.05  | American Samoa | 0.05  |
| Marshall Islands    | 0.05  | Northern Marianas | 0.05  | Isle of Man    | 0.05  |
| Australia           | 0.05  | Anguilla          | 0.07  | United States  | 0.07  |
| United Kingdom      | 0.09  | Guam              | 0.13  | New Zealand    | 0.17  |
| Denmark             | 0.18  | Nauru             | 0.19  | Sweden         | 0.21  |
| Malta               | 0.22  | Canada            | 0.25  | Norway         | 0.27  |
| Papua New Guinea    | 0.28  | Netherlands       | 0.29  | Cameroon       | 0.30  |
| Puerto Rico         | 0.31  | Gibraltar         | 0.33  | Austria        | 0.34  |
| Luxembourg          | 0.34  | Sierra Leone      | 0.34  | Finland        | 0.36  |
| Aruba               | 0.37  | Vanuatu           | 0.39  | Singapore      | 0.41  |
| Samoa               | 0.44  | Cyprus            | 0.45  | Slovenia       | 0.45  |
| Antigua and Barbuda | 0.45  | Bahamas, The      | 0.45  | Liberia        | 0.45  |
| Philippines         | 0.46  | Niue              | 0.47  | Hong Kong      | 0.48  |
| Micronesia          | 0.48  | Switzerland       | 0.48  | Germany        | 0.50  |
| Barbados            | 0.50  | Guyana            | 0.51  | Belize         | 0.51  |
| Trinidad and Tobago | 0.53  | Croatia           | 0.54  | Greece         | 0.55  |
| Zimbabwe            | 0.56  | Solomon Islands   | 0.56  | Estonia        | 0.59  |
| Seychelles          | 0.61  | Latvia            | 0.62  | Jordan         | 0.63  |
| France              | 0.64  | Spain             | 0.65  | Nigeria        | 0.65  |
| Ghana               | 0.66  | Poland            | 0.67  | Iraq           | 0.69  |
| Malaysia            | 0.69  | Belgium           | 0.69  | Brunei         | 0.70  |
| South Africa        | 0.71  | Lithuania         | 0.71  | Botswana       | 0.71  |
| Romania             | 0.71  | Tonga             | 0.72  | Portugal       | 0.72  |
| Egypt               | 0.72  | Chile             | 0.73  | Lebanon        | 0.73  |
| Suriname            | 0.74  | Italy             | 0.75  | Nepal          | 0.75  |
| Czech Republic      | 0.75  | Slovakia          | 0.76  | Mexico         | 0.77  |
| Argentina           | 0.77  | Bulgaria          | 0.78  | Colombia       | 0.78  |
| Cambodia            | 0.80  | Fiji              | 0.80  | Hungary        | 0.81  |
| India               | 0.82  | Peru              | 0.84  | Zambia         | 0.85  |
| Guatemala           | 0.87  | Kazakhstan        | 0.88  | Morocco        | 0.88  |
| Paraguay            | 0.88  | Sri Lanka         | 0.90  | Korea, South   | 0.90  |
| Tunisia             | 0.91  | Yemen             | 0.92  | Pakistan       | 0.92  |
| Algeria             | 0.93  | Kenya             | 0.93  | Uganda         | 0.93  |
| Russia              | 0.95  | Brazil            | 0.99  | China          | 1.00  |
| Japan               | 1.00  | Turkey            | 1.00  | Indonesia      | 1.00  |

*Notes:* This table reports country-level linguistic distance measures relative to the United States. Smaller values indicate countries or territories that are linguistically closer to the United States, while larger values indicate greater linguistic distance. The measure is normalized so that values are bounded between 0 and 1.

## C.2 Pairwise Linguistic Distance among Major Countries of Origin

Table C2: Pairwise Linguistic Distance among Major Countries of Origin

| Country Pair      | Pairwise Distance |
|-------------------|-------------------|
| China–South Korea | 0.99              |
| China–India       | 1.00              |
| China–Taiwan      | 0.30              |
| India–South Korea | 0.98              |
| India–Taiwan      | 1.00              |
| India–Iran        | 1.00              |

*Notes:* This table presents pairwise linguistic distance measures for selected major countries of origin. Higher values indicate that the two countries are linguistically more distant from each other. These measures are used to capture differences in linguistic backgrounds across origin-country groups.

## C.3 Country-of-Origin Mapping Used to Impute Missing Race/Ethnicity

Table C3: Country-of-Origin Mapping Used to Impute Missing Race/Ethnicity

| Region                  | Countries of origin                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              | Replaced<br>Race/Ethnicity |
|-------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------|
| Africa                  | Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Congo, Democratic Republic of the, Congo, Republic of the, Djibouti, Egypt, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, The, Ghana, Guinea, Guinea-Bissau, Ivory Coast, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, South Sudan, Sudan, Tanzania, Togo, Tunisia, Uganda, Zambia, Zimbabwe, Swaziland, Cote d'Ivoire | Black                      |
| Asia                    | Afghanistan, Armenia, Azerbaijan, Bahrain, Brunei, China, Iran, Iraq, Israel, Japan, Jordan, Kazakhstan, Kuwait, Kyrgyzstan, Lebanon, Mongolia, North Korea, Oman, Philippines, Qatar, Saudi Arabia, Singapore, South Korea, Syria, Tajikistan, Timor-Leste, Turkey, Turkmenistan, United Arab Emirates, Uzbekistan, Yemen, West Bank, Taiwan, Hong Kong, Gaza Strip                                                                                                                                                                                                                                                             | Asian                      |
| South Asia              | Bangladesh, Bhutan, Burma, Cambodia, India, Indonesia, Laos, Malaysia, Maldives, Myanmar, Nepal, Pakistan, Sri Lanka, Thailand, Vietnam                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          | South Asian                |
| Europe                  | Cyprus, Georgia, Russia, Albania, Andorra, Austria, Belarus, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Kosovo, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Moldova, Monaco, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, San Marino, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom, Vatican City, Yugoslavia, Macedonia, Federal Republic of Germany                                                                                  | White                      |
| Central & South America | Antigua and Barbuda, Bahamas, The, Barbados, Belize, Costa Rica, Cuba, Dominica, Dominican Republic, El Salvador, Grenada, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Trinidad and Tobago, Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela, British Virgin Island                                                                                                                                                                                                          | Hispanic                   |
| Oceania                 | Australia, Fiji, Kiribati, Marshall Islands, Micronesia, Nauru, New Zealand, Palau, Papua New Guinea, Samoa, Solomon Islands, Tonga, Tuvalu, Vanuatu                                                                                                                                                                                                                                                                                                                                                                                                                                                                             | White                      |
| North America           | Canada, United States                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            | White                      |

*Notes:* This table summarizes the country-of-origin mapping used to impute race/ethnicity when the administrative race/ethnicity variable is missing or reported as nonresident.