1-1-2013

When Do Faculty inputs Matter? A Panel Study of Racial/Ethnic Differences in Engineering Bachelor's Degree Production

Tafaya S. Ransom
University of Pennsylvania, ransomt@gse.upenn.edu

When Do Faculty inputs Matter? A Panel Study of Racial/Ethnic Differences in Engineering Bachelor's Degree Production

Abstract
Science, technology, engineering and mathematics (STEM) fields are widely credited as the primary drivers of economic growth through innovation, with engineering universally identified as especially critical. Yet as other nations have strengthened their engineering talent pools, the United States has struggled to cultivate an engineering workforce that reflects its diversity and takes full advantage of its human capital. Reflecting this dilemma, African Americans have consistently posted the weakest persistence and bachelor's degree completion rates of all racial/ethnic groups in engineering, and by some indications, their postsecondary outcomes are worsening.

The purpose of this study was to develop understanding about potential institutional levers for improving engineering bachelor's degree attainment both for underrepresented minorities (URMs) broadly and Black students specifically. Drawing on the higher education production function, I used multiple sources of institutional panel data for 324 engineering schools/colleges from 2005 to 2011 to uncover differential relationships between faculty predictors and engineering bachelor's degree production by student race/ethnicity and institutional context. I used multiple imputation to handle missing data and estimated fixed effects linear regression and dynamic panel models of engineering degree production, then I assessed institutions' degree production efficiencies using stochastic frontier analysis.

The findings indicate that from 2005 to 2011, the number of engineering bachelor's degrees conferred to Black students declined 10%, with the smallest declines occurring at highly competitive institutions (2%) and the largest declines at HBCUs (30%). Results from the fixed effects models indicate that engineering faculty-to-student ratio was positively related and the proportion of research faculty negatively related to engineering bachelor's degree production for every student subgroup in at least one institutional setting. The share of URM faculty was positively related to degree production for URMs and Blacks in some settings. However, no faculty measure was predictive of degree output for every student subgroup across every institution type. And in every instance where a faculty variable was related to degree output for multiple student subgroups, the magnitude of the estimated effect was greatest for Black students, then URMs, then all students. Ultimately, the study suggests that leveraging institutional resources to improve student outcomes in STEM calls for targeted analyses to develop strategies that reflect the heterogeneity of STEM disciplines, STEM students, and educational settings.

Degree Type
Dissertation

Degree Name
Doctor of Philosophy (PhD)

Graduate Group
Education

First Advisor
Laura W. Perna

Keywords
engineering education, faculty, higher education production function, panel data, STEM, underrepresented minorities

Subject Categories
Education Policy | Higher Education Administration | Higher Education and Teaching

WHEN DO FACULTY INPUTS MATTER? A PANEL STUDY OF RACIAL/ETHNIC DIFFERENCES IN ENGINEERING BACHELOR'S DEGREE PRODUCTION

Tafaya Ransom

A DISSERTATION

in

Education

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2013

Supervisor of Dissertation:

____

Laura W. Perna, Professor of Education

Graduate Group Chairperson:

____

Stanton E. F. Wortham, Professor of Education

Dissertation Committee:

Laura W. Perna, Professor of Education

Robert Boruch, Professor of Education and Statistics

Marybeth Gasman, Professor of Education

Levi T. Thompson, Professor of Chemical Engineering, University of Michigan

WHEN DO FACULTY INPUTS MATTER? A PANEL STUDY OF RACIAL/ETHNIC DIFFERENCES IN ENGINEERING BACHELOR'S DEGREE PRODUCTION

DEDICATION

To Laura Idella Grier, who made higher education a family value.

To Momma, Zaji, and Oni – we did it.

ACKNOWLEDGMENT

Many people played a role in making this work possible. I am indebted to my dissertation committee: Laura Perna (my chair), Marybeth Gasman, Bob Boruch, and Levi Thompson. Laura has truly helped me develop my ideas and my identity as a scholar – through her supportive and instructive mentorship and by the remarkable example she embodies. Marybeth, whose prolific work first drew me to the University of Pennsylvania, has pushed me to keep my work relevant and grounded in the issues that matter most to me. In and outside of class, Dr. Boruch has had a knack for opening my eyes to new insights and perspectives, which have helped me think through this study and other matters. And Levi, who first introduced me to the notion of higher education research, has been an instrumental advisor, larger-than-life role model, and strong advocate throughout my journey from chemical engineer to education researcher.

I am also grateful to other teachers and mentors who have played a critical role in getting me to this milestone – particularly, Jale and Ates Akyurtlu, Adeyinka Adeyiga, Morris Morgan, and Al Colón from my days at Hampton University; Pat Kinney and Pauline Bigby at the University of Michigan; Shaun Harper, Joni Finney, Matt Hartley, Karen Carter, Henry May, and Paul Allison at the University of Pennsylvania; Jackie Muhammad, Cory Phillips, Valarie Thomas, Stacey Nunley, Matt Van Italie, and John Sylvanus Wilson.

Many thanks as well to the University of Pennsylvania Graduate School of Education (GSE) for giving me the opportunity (and Dean's fellowship) to pursue this dream and the community of scholars at GSE who inspired and challenged me along the way. I am especially grateful to the U.S. Department of Education Institute for Education Sciences (IES) for their vital support of the University of Pennsylvania's Pre-doctoral Training Program in Interdisciplinary Methods for Field-Based Research in Education. As an IES Pre-doctoral fellow, I have benefited not only from financial support but also countless enriching experiences.

I am ever thankful for friends and family whose love and prayers carried me through this process. Over the last two and half years especially, I have been humbled, affirmed, and spurred on by the unwavering support of my closest friends, my uncle and aunties, cousins, nephews, niece, sisters, brother, and mother. To my sister Shanee and my brother Paul, you'll never know how much I love, admire, and appreciate you both. To know you are always in my corner gives me peace and strength. To Zaji and Oni, my beautiful twins – you made this experience so much richer and more important.

Finally, even though I came up with more than 53,000 words in writing this dissertation, I can't come up with any that are adequate to fully capture the depth of my gratitude for the constant and selfless support of my mother, Rhonda Grier. I have always relished the occasions when people have commented that I look like, sound like, or am in any way similar to my mother. But the longer and better I know my mother, the more I realize how difficult a task it will be to ever measure up to the woman she is.

To God be the glory.

The research reported here was supported in part by the Institute of Education Sciences, U.S. Department of Education, through Grant #R305B090015 to the University of Pennsylvania. The opinions expressed are those of the authors and do not represent the views of the Institute or the U.S. Department of Education.

ABSTRACT

WHEN DO FACULTY INPUTS MATTER? A PANEL STUDY OF RACIAL/ETHNIC DIFFERENCES IN ENGINEERING BACHELOR'S DEGREE PRODUCTION

Tafaya Ransom

Laura W. Perna

Science, technology, engineering and mathematics (STEM) fields are widely credited as the primary drivers of economic growth through innovation, with engineering universally identified as especially critical. Yet as other nations have strengthened their engineering talent pools, the United States has struggled to cultivate an engineering workforce that reflects its diversity and takes full advantage of its human capital. Reflecting this dilemma, African Americans have consistently posted the weakest persistence and bachelor's degree completion rates of all racial/ethnic groups in engineering, and by some indications, their postsecondary outcomes are worsening.

The purpose of this study was to develop understanding about potential institutional levers for improving engineering bachelor's degree attainment both for underrepresented minorities (URMs) broadly and Black students specifically. Drawing on the higher education production function, I used multiple sources of institutional panel data for 324 engineering schools/colleges from 2005 to 2011 to uncover differential relationships between faculty predictors and engineering bachelor's degree production by student race/ethnicity and institutional context. I used multiple imputation to handle missing data and estimated fixed effects linear regression and dynamic panel models of

engineering degree production, then I assessed institutions' degree production efficiencies using stochastic frontier analysis.

The findings indicate that from 2005 to 2011, the number of engineering bachelor's degrees conferred to Black students declined 10%, with the smallest declines occurring at highly competitive institutions (2%) and the largest declines at HBCUs (30%). Results from the fixed effects models indicate that engineering faculty-to-student ratio was positively related and the proportion of research faculty negatively related to engineering bachelor's degree production for every student subgroup in at least one institutional setting. The share of URM faculty was positively related to degree production for URMs and Blacks in some settings. However, no faculty measure was predictive of degree output for every student subgroup across every institution type. And in every instance where a faculty variable was related to degree output for multiple student subgroups, the magnitude of the estimated effect was greatest for Black students, then URMs, then all students. Ultimately, the study suggests that leveraging institutional resources to improve student outcomes in STEM calls for targeted analyses to develop strategies that reflect the heterogeneity of STEM disciplines, STEM students, and educational settings.

TABLE OF CONTENTS

DEDICATION III

ACKNOWLEDGMENT IV

ABSTRACT VII

LIST OF TABLES XII

LIST OF FIGURES XV

CHAPTER 1 – INTRODUCTION 1

The Importance of Considering Engineering 2

The Importance of Considering Institutional Performance in Engineering Education 6

The Importance of Considering African American Outcomes in Engineering 9

Potential Institutional Levers for Addressing the Underrepresentation of African Americans in Engineering 13

Purpose of the Study 16

Significance of the Study 18

Organization of the Dissertation 19

CHAPTER 2 – REVIEW OF THE LITERATURE 20

An Orientation to Research on Science and Engineering Postsecondary Education 20

Theoretical Perspectives Used to Examine STEM Retention, Completion, or Degree Production 22
Interactionalist frameworks. 22
Organizational frameworks. 23
Higher education production functions. 24

Known Institutional Predictors of STEM Persistence, Completion, or Degree Production 27
Selected qualitative findings. 27
Institutional inputs. 31
Institutional characteristics. 59
Aggregate student characteristics 72

Summary of Current Research 73

Limitations of Current Research 75

Need for Additional Research 77

CHAPTER 3 – RESEARCH DESIGN 79

Research Questions 79

Data 80

Sample 83

Variables 86
Dependent (output) variables. 86
Independent variables. 88
Summary of variables. 93

Analytic Methods 97
Missing data. 97
Research question #1: Trends in engineering degree output and faculty inputs. 100
Research question #2: Estimating an engineering degree production function. 101
Research question #3: Assessing degree production efficiency. 112
Multiple comparisons. 116

Limitations 118

CHAPTER 4 – FINDINGS 122

Research Question #1: Trends in Engineering Degree Output and Faculty Inputs 122

Research Question #2: Estimating an engineering degree production function 130
Variations in faculty effects by student race/ethnicity. 132
Variations in faculty effects by student race/ethnicity and institutional context. 136
Alternative inputs models. 148
Dynamic panel model of engineering degree production. 151

Research Question #3: Assessing Degree Production Efficiency 156

CHAPTER 5 – CONCLUSIONS 169

Summary of Findings 169
Variations in inputs and outputs at engineering schools and colleges (RQ# 1). 169
Which faculty inputs matter for whom and in which contexts (RQ# 2)? 171
Gaining insights from analyzing efficiencies (RQ# 3). 175

Discussion 176

Contribution 177

Policy Recommendations 179

APPENDIX 184

BIBLIOGRAPHY 197

LIST OF TABLES

Table 1.1 Racial/ethnic distribution (percent) of U.S. residential population, college graduates, S&E degree holders, S&E occupations, and engineering occupations: 2008. . 6

Table 3.1 ASEE engineering disciplines. 84

Table 3.2 Summary of complete sample, ASEE participant institutions, 2005-2011. 85

Table 3.3 Quartile cut-points for total number of engineering bachelor's degrees conferred to underrepresented minorities and African Americans during 2005to 2011 and number of institutions (and observations) in each quartile. 86

Table 3.4 Variables used to model engineering degree production 95

Table 4.1 Descriptive Statistics for all variables used in the study. 124

Table 4.2 Number of bachelor's degrees and average faculty inputs across all sample institutions. 127

Table 4.3 Change in number of bachelor's degrees awarded and average faculty inputs from 2005 to 2011, by student race/ethnicity and institutional contexts. 128

Table 4.4 Fixed effects estimates of log engineering bachelor's degrees by student race/ethnicity using full sample (all institutions) and 20 imputed data sets. 135

Table 4.5 Fixed effects estimates of log engineering bachelor's degrees to ALL STUDENTS by institutional control, institutional selectivity, and Carnegie classification using 20 imputed data sets. 138

Table 4.6 Fixed effects estimates of log engineering bachelor's degrees to URM STUDENTS by institutional control, institutional selectivity, and Carnegie classification using 20 imputed data sets. 142

Table 4.7 Fixed effects estimates of log engineering bachelor's degrees to BLACK STUDENTS by institutional control, institutional selectivity, and Carnegie classification using 20 imputed data sets. 146

Table 4.8 Fixed effects estimates of log engineering bachelor’s degrees by student race/ethnicity and institutional control, using capital inputs and 20 imputed data sets. . 149

Table 4.9 Fixed effects estimates of log engineering bachelor’s degrees by student race/ethnicity and institutional control, using capital and faculty inputs and 20 imputed data sets. 149

Table 4.10 Fixed effects estimates of log engineering bachelor’s degrees by student race/ethnicity and institutional control, using broad institutional inputs, faculty inputs, and 20 imputed data sets. 151

Table 4.11 Arellano-Bond tests for serial correlation for dynamic models of log engineering bachelor's degrees by race/ethnicity and institutional control. 153

Table 4.12 Arellano-Bond tests for serial correlation for dynamic models of log engineering bachelor's degrees to URMs, including 2 lags of the dependent variable. . 154

Table 4.13 Dynamic estimates of log engineering degrees by race/ethnicity and institutional control using unimputed data. 155

Table 4.14 Stochastic frontier production model estimates by race/ethnicity for the full analytic sample. 157

Table 4.15 Descriptive statistics for technical efficiency (TE) estimates for time-invariant SFA degree production models. 158

Table 4.16 Average number of degrees and efficiency scores for top 50 engineering bachelor’s degree producers by student race/ethnicity, 2005 to 2011, ... 159

Table 4.17 Top 50 producers of engineering bachelor's degrees to URM students, by absolute number of degrees and technical efficiency (TE), 2005 to 2011. 161

Table 4.18 Top 50 producers of engineering bachelor's degrees to BLACK students, by absolute number of degrees and technical efficiency, 2005 to 2011. 166

Table A.1 Engineering schools/colleges included in the study by state. 184

Table A.2 Decomposed descriptive statistics for outcome and explanatory variables, computed to confirm variation over time. 191

Table A.3 Hausman Test comparing fixed effects and random effects estimates of log engineering degree production for URM students. 193

Table A.4 Sensitivity analysis: Faculty-to-student ratio (Fixed effects estimates of log engineering degree bachelor's degrees to URM students using pooled sample of institutions and 20 imputed data sets). 194

Table A.5 Sensitivity analysis: Same-race predictors (Fixed effects estimates of log engineering degree bachelor's degrees to BLACK students by institutional context using 20 imputed data sets). 195

LIST OF FIGURES

Figure 1.1 Percentage of first university degrees in science and engineering: 2008 (or most recent year available). 4

Figure 1.2 Share of engineering bachelor's degrees awarded to underrepresented minorities, 1990-2010. 11

Figure 1.3 Number of engineering bachelor's degrees awarded to African Americans, 1990-2010. 12

Figure 3.1 Measures of technical efficiency 113

Figure 3.2 Traditional and stochastic frontier production functions. 115

Figure 5.1 Summary matrix of faculty input effects by institutional context and student race/ethnicity. 172

Figure A.1 Histograms of model variables before and after log transformations: number of bachelor's degrees to all students, URM students, and African American students. 189

Figure A.2 Histograms of model variables before and after log transformations: total FTE engineering undergraduates, URM FTE engineering undergraduates, number of full-time Ph.D. students. 190

CHAPTER 1 – INTRODUCTION

In 1987, Robert M. Solow won the Nobel Prize in Economic Sciences for his contributions to the theory of long-term macroeconomic growth. Solow's work showed that the primary force behind sustained economic growth is technological progress, which in the broadest sense encompasses invention, innovation and the diffusion of technology and which his growth models suggested explained more than 80% of the United States' economic growth during the first half of the twentieth century[1] (Solow, 1957, 1987). The basic premise of Solow's technological framework of economic growth endures not only in the abstract world of macroeconomic theory but is at the heart of the United States' and other developed and emerging nations' economic competitiveness agendas (Mokyr, 2002; Nelson, 1993; U.S. Department of Commerce, 2012).

Science, technology, engineering and mathematics (STEM) fields are widely credited as the primary drivers of economic growth through innovation (National Academy of Sciences, 2007, 2010; National Economic Council, Council of Economic Advisers, & Office of Science and Technology Policy, 2011; U.S. Department of Commerce, 2012). And in today's technology-driven world, these fields are perhaps even more vital to economic growth and job creation than in years past. Add to that the increasingly global nature of the economic marketplace, and the result is an intense international contest to develop STEM talent.

---

[1] Other economists attribute economic growth to technological progress to varying degrees depending upon the underlying assumptions of their respective models. By most indications, technological progress is responsible for one quarter to one half of the U.S.'s economic growth rate since World War II. See for example Abramovitz (1986) and Mokyr (1990).

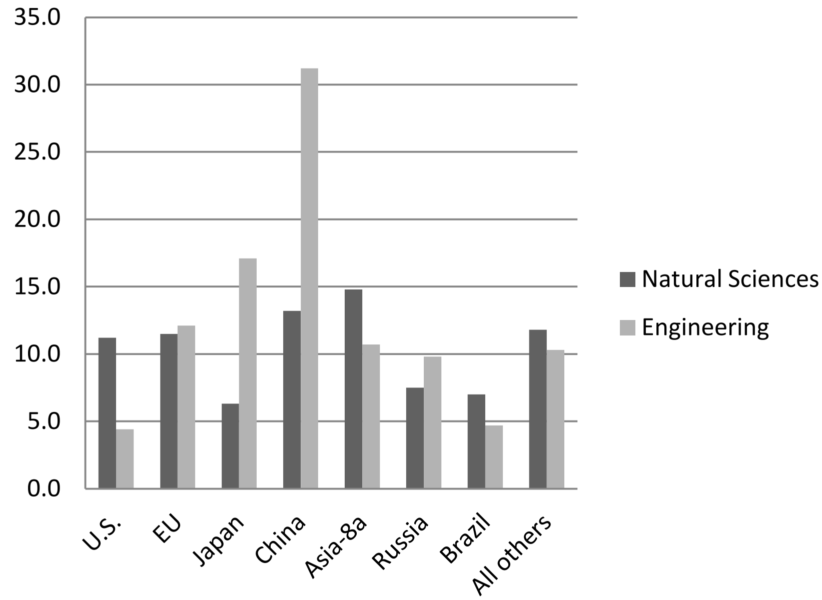
Over at least the last thirty years, however, numerous reports have sounded alarms about the United States' ability to cultivate STEM talent (National Science Foundation, 1982; National Science Board, 1986; National Academy of Sciences, 2007). Central to these reports are several interrelated threats to U.S. innovative capacity: an aging STEM workforce (e.g., Butz et al., 2004); the propensity for students and workers to leave STEM fields and careers (e.g., Carnevale, Smith, & Melton, 2010); declining interest in STEM fields among U.S. citizens and permanent residents (e.g., National Academy of Sciences, 2010); growing uncertainty associated with reliance on foreign-born talent to supplement the domestic STEM workforce (e.g., National Academy of Sciences, 2007; 2010); and drastic demographic shifts in which the fastest growing segments of the population are those traditionally underrepresented in STEM fields (e.g., National Academy of Sciences, 2011).

The Importance of Considering Engineering

Among the STEM disciplines, engineering is universally identified as especially critical to technology-driven economic growth, as engineers develop new manufacturing processes and products; create, distribute and manage energy, transportation and communications systems; prevent new and redress old environmental problems; create pioneering health care devices; and, generally, make technology work (ASEE, 2010). In fact, past national chairman of the National Academy of Engineering, Richard Morrow (1994) remarked, "the nation with the best engineering talent is in possession of the core ingredient of comparative economic and industrial advantage" (p. 16). Recent reports published by the National Academy of Engineering (2003, 2008) synthesize the broad scope of engineering in terms of specific products and processes of the past as well as looming 21st Century challenges. Others also provide compelling evidence of the important functions engineers serve (see, for example, Augustine, 2011; Petroski, 2010) and the extent to which engineers are highly sought-after in both technical and non-technical sectors of the U.S. workforce (Identified, 2011).

Yet as other nations have strengthened their engineering talent pools, the United States appears to be falling behind. Figure 1.1 shows that although the U.S. produces natural science graduates at rates comparable to other nations, the share of engineering graduates among first university degree recipients was lower in the United States (4.7%) than in the European Union (12.1%), Japan (17.1%), China (31.2%) or any other country or group of countries included in the most recent National Science Foundation tabulations of international science and engineering higher education indicators (National Science Board, 2012).

Figure 1.1 Percentage of first university degrees in science and engineering: 2008 (or most recent year available).



*Asia-8a includes Bangladesh, Brunei, Cambodia, China, India, Japan, Kyrgyzstan, Laos, Malaysia, Mongolia, Philippines, Singapore, South Korea, Taiwan

Source: Appendix Table 2-32, National Science Board, 2012.

These unfavorable international indicators reflect domestic challenges in engineering education. For example, while the number of all bachelor's degrees awarded in the U.S. increased by 60% between 1985 and 2008, the number of engineering bachelor's degrees awarded in the U.S. fell by 11% over that time. As a result, the percentage of U.S. bachelor's degrees that were conferred in engineering declined from 8% to 4% during 1985 to 2008 (National Science Foundation, 2011a). And although the number of engineering doctorate degrees conferred in the U.S. increased 148% between 1985 and 2008, temporary visa holders received 61% of the degrees awarded in 2008, up from 45% in 1985 (National Science Board, 2008; National Science Foundation, 2011b).

These trends have led to a host of recent efforts to increase the number of engineering graduates in the U.S. For example, in 2011, President Barack Obama's Council on Jobs and Competitiveness rolled out the 10,000 Engineers Initiative to increase the nation's annual engineering degree production rate by as much, with help from private partners (Jobs Council, 2011). Also in 2011, Kansas enacted multi-year legislation, the University Engineering Initiative, to increase the number of engineering graduates in the state by over 50% in ten years (Kansas Board of Reagents, 2011). And other states (e.g., Utah, Alaska, Alabama, Texas, and Virginia) have similar policies to boost engineering degree production.

But improving the nation's fortunes in engineering also requires addressing the enduring struggle to cultivate an engineering workforce that reflects the diversity of the United States and takes full advantage of the nation's talent base. For example, although the number of women in engineering occupations increased by more than 100,000 workers over the past twenty-five years, women held only 11% of engineering jobs in 2009. Yet they made up 44% of the entire college-educated workforce (National Science Board, 2012; National Science Foundation, 2011b). Similarly, Table 1.1 shows that American Indians/Alaska Natives, African Americans, and Hispanics are underrepresented in STEM in general and engineering in particular relative to both their representation in the U.S. residential population and among college degree holders. And at just 26% of parity with their share of the U.S. resident population, African Americans are the least well-represented racial/ethnic group in the engineering workforce (Table 1.1).

Table 1.1 Racial/ethnic distribution (percent) of U.S. residential population, college graduates, S&E degree holders, S&E occupations, and engineering occupations: 2008.

Race/ethnicity	Total U.S. residential population	College degree holders	S&E degree holders	S&E occupations	Engineering occupations	Engineering Parity (Engineering/Population)
Asian	4.7	8.5	11.2	16.9	15.6	3.3
American Indian/Alaska Native	0.7	0.3	0.4	0.3	0.2	0.29
Black	11.7	7.2	5.5	3.9	3.1	0.26
Hispanic	13.9	6.2	5.6	4.9	5.6	0.40
White	67.6	76.5	75.2	71.8	73.4	1.1
Native Hawaiian/Other Pacific Islander	0.1	0.1	0.4	0.4	0.6	6.0
Two or more races	1.2	1.1	1.7	1.7	1.6	1.3

Note: Tabulations based on data provided in National Science Board (2012).

The Importance of Considering Institutional Performance in Engineering Education

The evidence laid out so far suggests that engineering education faces dynamic challenges on multiple fronts: rapid technological advances that trigger evolving roles and responsibilities for technical professions; globalization; ambitious national goals and prioritization of engineering by various constituencies; and shifting demographics favoring groups whose talents have historically been woefully underutilized in engineering. In a broader climate of increasing accountability and fiscal pressure in higher education, these challenges raise expectations for engineering education to do more (productivity) and better (quality) with less (efficiency) (Alexander, 2000; Chubin, May, & Babco, 2005). For those with a stake in the future of U.S. engineering – business and civic leaders, federal and state governments, institutional trustees and leaders, ABET (formerly the Accreditation Board for Engineering and Technology, Inc.), faculty and students, and the public at large – accountability for performance outcomes rests at the institutional level.

Lessons from the broader higher education research literature can help guide the engineering education community as it ponders how to assess institutions and hold them to account for producing more engineers. First, higher education research has established that use of raw graduation, completion rates, or even degree counts to assess institutional performance can be misleading (DeAngelo, Franke, Hurtado, Pryor, & Tran, 2011). For example, roughly two thirds or more of the variation between institutions in graduation rates is attributable to differences between students' entering characteristics rather than "differential institutional 'effects'" (Astin & Oseguera, 2005, p.45). Therefore, institutions should not be judged or compared based on their degree completion rates without adjusting for students' entering characteristics.

Still, that at least one third of the variation in institutional degree completion rates is not explained by student characteristics means that "institutional effects" do matter. In other words, there is room to improve institutional performance without simply raising admissions standards. For example, emerging higher education research has found that institutional expenditures can have differential, statistically significant relationships with institutional graduation rates depending on the functional category of spending (e.g., instruction, academic support, student services, research) (Webber & Ehrenberg, 2010; Chen, 2012; Webber, 2012). Much of this work is grounded in microeconomic producer theory and involves estimating higher education production functions (Hopkins, 1990). These higher education production function studies occasionally include efficiency analyses (e.g., Blose, Porter, and Kokkelenberg, 2006). Efficiency studies can show, for example, that two institutions that are ostensibly similar produce different levels of educational output (e.g., graduation rates) using the same level of inputs (e.g., instructional expenditures). Such investigations might lead to replicating best practices from more efficient institutions at less efficient peer institutions.

Still, compared to traditional student-centered persistence/retention literature, there has been no systematic exploration of the potential of institutional context on student outcomes in the higher education literature (Titus, 2004). And with respect to STEM higher education research, Eagan (2010) contends that institutional forces are "at best under-studied or at worst ignored" (p. 2). In recent years, scholars have begun to address this gap in the knowledge through various studies of how institutional factors shape underrepresented minority (URM) outcomes in STEM (Malcom, 2008, 2010; Hurtado et al, 2009; Perna et al., 2009; Eagan, 2010; Hurtado, Newman, Tran, & Chang, 2010; Museus & Liverman, 2010; Hubbard & Stage, 2010; Ong, Wright, Espinosa, & Orfield, 2011; Ostreko, 2012). Yet few researchers disaggregate STEM into specific fields or URM into specific racial/ethnic groups.

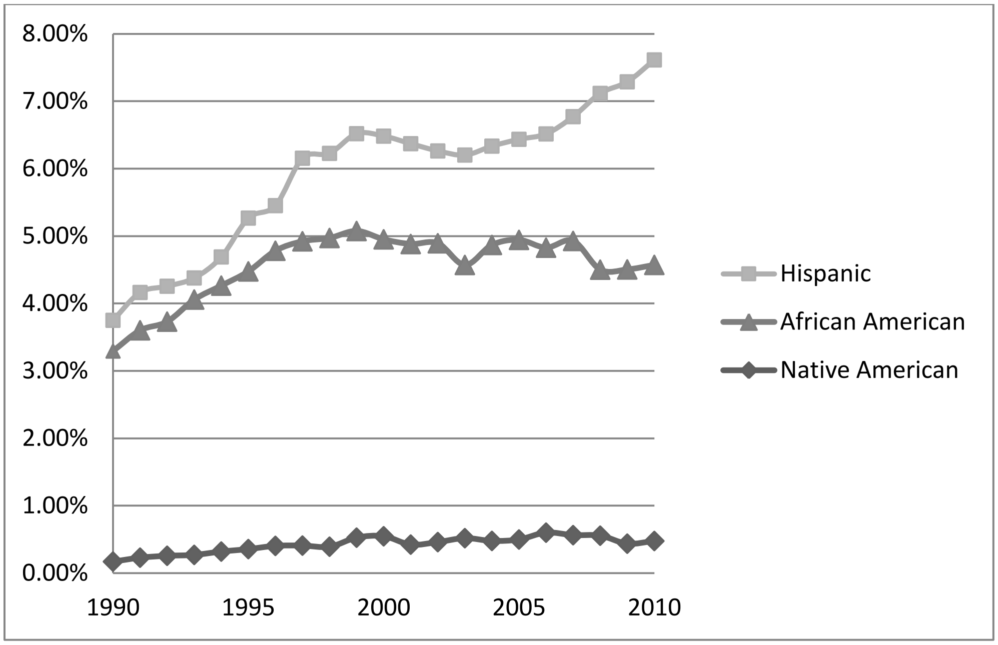
Engineering education research, however, still focuses almost exclusively on student-level predictors and outcomes and largely neglects institution- or multi-level analyses (Leetaru, 2010). Ultimately, meeting the demands for accountability and designing effective institutional strategies for improving URM student outcomes in engineering, requires distilling what matters to institutional performance along these lines. This means that research must consider which institutional levers offer promise for creating the conditions for success in engineering by examining relationships between *institutional* predictors and outcomes in engineering, rather than simply those at the individual student level.

The Importance of Considering African American Outcomes in Engineering

African Americans have consistently posted the weakest persistence and bachelor's degree completion rates of all racial/ethnic groups in engineering. The National Action Council for Minorities in Engineering (2012) reported that compared to all other racial/ethnic groups, Black engineering students are less likely to complete their degrees, take longer to complete their degrees, and more often transfer out of bachelor's degree programs into associate's degree or certificate programs. Other research confirms that African American engineering students have graduation rates substantially lower than all other groups (Georges, 1999; Brown, Morning, & Watkins, 2005; Morse & Babcock, 2009). For example, Morse and Babcock (2009) reported a six-year graduation rate of 31% for African American engineering students compared to 68% for non-minorities and 45% for Hispanics.

By some indications, African American postsecondary outcomes in engineering are worsening. Recent trends suggest a reversal of the modest gains achieved in the share of engineering bachelor's degrees awarded to African Americans during the 1990s (National Science Board, 2012). For example, based on data tabulated by NSF, Figure 1.2 shows that the share of engineering bachelor's degrees awarded to African Americans rose from 3.3% in 1990 to 5.1% by 1999, but declined to 4.6% by 2010 (i.e., a 10% decrease) (National Science Foundation, 2011b). The National Action Council for Minorities in Engineering's (2011) analysis of engineering degree trends indicates that African American representation among engineering baccalaureates declined 16% between 2000 and 2010. And more recent data from the American Society for Engineering Education suggests a 22% decline in representation between 2002 and 2011 (Yoder, 2012). These recent trends stand in contrast to the consistent (though oftentimes modest) gains in Hispanic and Native American engineering baccalaureate attainment since the 1990s (National Science Foundation, 2011b).

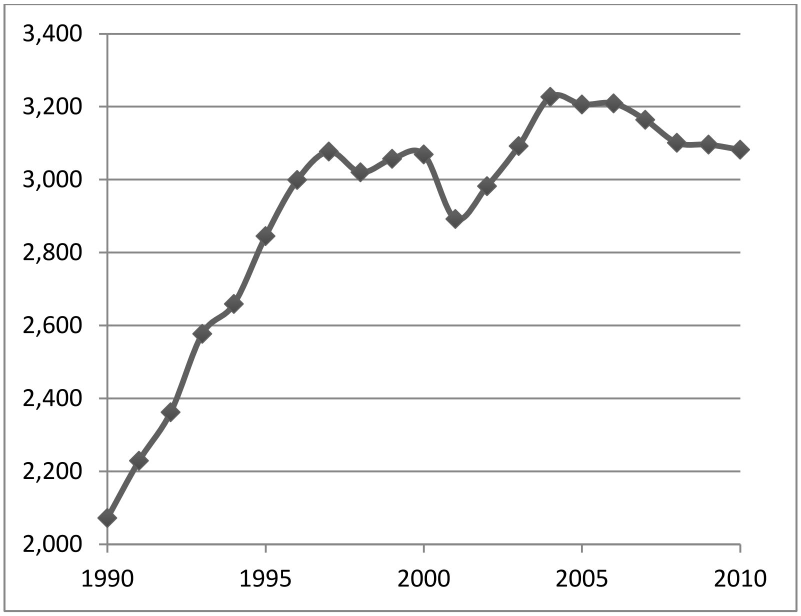
Figure 1.2 Share of engineering bachelor's degrees awarded to underrepresented minorities, 1990-2010.



Note: Based on data provided in National Science Foundation (2011b).

Given the relative growth of Latinos in the U.S. population in general and in higher education specifically (National Science Foundation, 2011b), it might be expected that African Americans would constitute a stable or even declining share of engineering baccalaureates. However, regressive national trends are also apparent in the absolute numbers of African Americans earning engineering bachelor's degrees. Degree completions data from the National Center for Education Statistics' Integrated Postsecondary Education Database (IPEDS) show a steep, upward trend in the number of engineering bachelor's degrees conferred to African Americans that slowed around 1997 and has been in reverse since at least 2004 (Figure 1.3).

Figure 1.3 Number of engineering bachelor's degrees awarded to African Americans, 1990-2010.



Note: Tabulated from IPEDS Completions Survey via NSF WebCASPAR data system.

In fact, drawing on multiple data sources, Weinberger (2011) charts a rapid growth in the number of Black engineering baccalaureates beginning in the 1970s through the early 2000s. She traces this period of growth to organized, well-funded efforts that were propelled by a coalition of corporations, professional organizations, and foundations. These efforts, which date back to the 1970s, began in response to the shifting political climate toward equal employment opportunities (Wilburn, 1974). Whether to change the opportunity structure or simply avoid potential sanctions, engineering education stakeholders engaged several key strategies to stimulate African American participation in engineering. These strategies included: expanding and improving engineering programs at historically Black colleges and universities (HBCUs); establishing dual degree partnerships between engineering institutions and HBCUs without engineering programs; providing minority engineering scholarships to prospective students; and providing financial incentives to engineering schools and colleges to expand minority recruiting and retention efforts (see, for example, American Society for Engineering Education, 1974; Lusterman, 1979; Blackwell, 1981; Blackwell, 1987). Weinberger's (2011) preliminary analysis of engineering degree trends indicates that these efforts corresponded with a clear uptick in African American participation in engineering.

Potential Institutional Levers for Addressing the Underrepresentation of African Americans in Engineering

Empirical research examining African American experiences and outcomes specifically in engineering is scarce (studies identified include: Good, Haplin, & Haplin, 2002; Moore, Madison-Colmore, & Smith, 2003; Brown, Morning, & Watkins, 2005; Moore, 2006; Slaughter, 2009; Newman, 2011a; 2011b). The available research consistently points to the importance of Black engineering students' interactions with faculty inside and outside of the classroom in positively or negatively shaping their sense of belonging (e.g., Good, Haplin, & Haplin, 2002), perception of the academic climate (Brown, Morning, & Watkins, 2005), and persistence in engineering (Newman, 2011a, 2011b). However, these studies are largely small-scale, qualitative, and centered around students enrolled at a single institution. Multi-institutional studies that consider African American outcomes in engineering offer only qualitative findings about the influence of faculty without direct quantitative measures to test potential relationships (Brown, Morning, & Watkins, 2005; Newman, 2011a).

Other research emphasizes the importance of faculty for African American outcomes in STEM more broadly. In particular, qualitative research that examines the role of HBCUs in STEM higher education (for example, Brazziel & Brazziel, 1997; Culotta, 1992; Southern Education Foundation, 2005; Perna et al., 2009) or compares Black students' experiences in STEM at HBCUs and non-HBCUs (for example, Wenglinsky, 1997; Suitts, 2003; Fries-Brit, Younger, & Hall; 2010; Lent et al., 2005; Brown, Morning, & Watkins, 2005) calls attention to the role of faculty. For example, Perna and colleagues' (2009) case study highlighted the importance of small class sizes, faculty availability, faculty encouragement, and undergraduate research as critical to students' success in the sciences at Spelman College, a historically Black women's college. Researchers have also found that compared to non-HBCUs, HBCUs offer students more academically supportive environments via positive interactions with faculty (and peers) (Fries-Brit, Younger, & Hall, 2010; Hurtado et al., 2009; Lent et al., 2005; Brown, Morning, & Watkins, 2005).

Moreover, research links positive interactions with STEM faculty – in the classroom, laboratory, and elsewhere – to self-efficacy, achievement, scientific identity development, and career expectations for underrepresented minorities in general (Santiago & Einarson, 1998; Carter 2002; Cole & Espinoza, 2008; Fries-Britt, 1998; Fries-Britt, Younger, & Hall, 2010; Hurtado et al., 2009; Thiry & Larsen, 2011; Leggon, 2010). Some research indicates that these positive outcomes are more pronounced when students interact with same-race faculty (Fries-Britt, 1998; Fries-Britt, Younger, & Hall, 2010; Griffin, Perez, Holmes, & Mayo, 2010; Price, 2010; Cole & Espinoza, 2008; Newman, 2011a).

Scholars often recommend further research examining the role of faculty (Hubbard & Stage, 2010; Perna et al., 2009; Newman, 2011a), presumably because much of the available research represents single institutions or relatively small samples of students and/or institutions. But what insights point to broadly available proxy measures to investigate the role of faculty on a larger scale, and in different institutional contexts? As it turns out, a few recent quantitative studies have examined institutional graduation and degree production rates for underrepresented minorities in STEM using various faculty-related predictors.

Student-faculty ratios have been used to represent the extent of student interactions with faculty (Dolan & Schmidt, 1994; Sibulkin & Butler, 2011; Chen 2012); faculty racial composition has been used to approximate the extent of same-race interactions or availability of same-race role models (Price, 2010; Hubbard & Stage, 2010; Ostreko, 2012); the proportion of part-time faculty or proportion of faculty by rank has represented the quality of student-faculty interactions (Eagan, 2010; Ostreko, 2012); and the ratio of research to instructional expenditures has been used to reflect institutional commitment to research relative to teaching, hence diminished opportunities for faculty-student interaction (Griffith, 2010). In this way, these studies offer more generalizable findings and – to a degree – partial tests of the insights gleaned from qualitative studies. Findings indicate that lower student-faculty ratios (Sibulkin & Butler, 2011), higher proportions of URM faculty (Price, 2010; Hubbard & Stage, 2010; Ostreko, 2012), higher proportions of tenured/tenure track faculty, and lower proportions of part-time faculty (Eagan, 2010; Ostreko, 2012) were associated with higher graduation and degree production rates for underrepresented minorities in STEM, while research-to-instructional expenditures was differentially related to STEM persistence and graduation depending on enrollment level (Griffith, 2010). Yet none of these studies investigated potential differences in the role of faculty across different subcategories of STEM and URM.

Purpose of the Study

This study is driven by the juxtaposition of the need for developing a highly-skilled and more diverse U.S. engineering workforce with the persistently meager, ostensibly worsening, outcomes for African Americans in undergraduate engineering education. Available STEM higher education research offers instructive insights. However, its emphasis on student-level predictors and outcomes and broad conceptualizations of "STEM" and "URM" has left gaps in the knowledge about potential institutional levers for improving higher education performance in specific STEM disciplines and with respect to specific student populations.

A review of recent research exploring relationships between institutional structures and context and URM outcomes in STEM as well as the origins of past improvements in African American attainment in engineering points to faculty as an under-investigated potential policy lever for shaping student outcomes in STEM. No research identified examines faculty predictors with respect to African Americans outcomes in a particular discipline or the degree to which faculty measures matter within different types of institutions. Therefore, the purpose of this study is to uncover differential relationships between faculty predictors and engineering bachelor's degree production by student race/ethnicity and institutional context. The study is particularly designed to disentangle potential racial/ethnic differences in engineering bachelor's degree production both in terms of a) underrepresented minorities relative to all students and b) Black students relative to URM students.

Drawing on the higher education production function augmented by other disciplinary perspectives and empirical evidence, this study uses multiple sources of institutional panel data and appropriate multivariate statistics to understand the extent to which faculty "inputs" matter for predicting engineering bachelor's degree "output" at different types of postsecondary institutions. Specifically, the analyses combine data from the American Society for Engineering Education's (ASEE) annual Survey of Engineering and Engineering Technology Colleges, the National Science Foundation's Higher Education Research & Development Survey, and the U.S. Department of Education National Center for Education Statistics' Integrated Postsecondary Education Database (IPEDS) and Delta Cost Project database over the seven-year period from 2005 to 2011 to address the following research questions:

1. How did engineering colleges and schools' bachelor's degree output by race/ethnicity and selected faculty inputs vary during the study period, 2005 to 2011? Were these trends consistent across institutional contexts?
2. Do engineering colleges/schools' faculty inputs similarly predict bachelor's degrees production for all students, underrepresented minorities, and African

Americans, controlling for characteristics of the college/school and broader institutional characteristics?

3. To what extent are engineering colleges/schools maximizing bachelor's degree production for underrepresented minorities and African Americans based on the models specified in RQ2?

Significance of the Study

Expanding access and success for underrepresented minorities in science, technology, engineering, and mathematics continues to garner the attention and investment of myriad stakeholders (National Academy of Sciences, 2011). And among the STEM disciplines, engineering stands out both in its critical role in sustaining the nation's innovative capacity and its distinction as one of the least diverse STEM disciplines at all levels of education and the workforce. Yet despite more than 30 years of research and policy efforts, the most recent decade has witnessed consistent declines in numbers and shares of engineering bachelor's degrees awarded to African Americans.

Available STEM higher education research offers instructive insights, yet there remain gaps in the knowledge about how factors within the direct control of institutions might be leveraged to improve institutional performance, especially for specific STEM disciplines and student populations. Therefore, this study departs from previous research on underrepresented minority student success in STEM in at least four important ways. First, I disaggregate both STEM fields and underrepresented minorities to illuminate some of the nuances that might be washed out when researchers use aggregated measures. Second, I draw on under-utilized, publicly available, recent institutional panel data. Third, I explicitly deal with missing data and match the panel data with appropriate analytic methods to partially alleviate the problem of omitted variables bias (the operative word being "partially") (Allison, 2009). Fourth, rather than focusing on how individual *student* predictors influence *student* outcomes, I examine *institutional* performance in engineering, which is appropriate in a climate increasing accountability and which adds another dimension to the knowledge about how *institutional* forces shape student outcomes in STEM fields.

Organization of the Dissertation

With the close of this introductory chapter, Chapter 2 picks up with a review of the guiding theoretical perspectives and empirical findings from research examining the influence of institutional factors on institutional performance outcomes, mainly in STEM higher education but also, to a limited extent, in the broader higher education literature. In Chapter 3, I discuss my research design, including the research questions; the data sources, analytic sample, and variables used in the study; and the analytic methods used to address each research question. In Chapter 4, I present the results of the study, organized around each research question. Lastly, Chapter 5 concludes with a discussion of the results, followed by a summary of the contributions of the study, suggested directions for future research, and policy recommendations.

CHAPTER 2 – REVIEW OF THE LITERATURE

Existing research examines at least three varieties of institutional outcomes that have resonance with the present investigation of engineering degree production: retention or student persistence rates; graduation or degree completion rates; and degree production, productivity, and/or efficiency. Each of these outcomes reflects a different take on student success and offers insights about institutional performance. This chapter reviews guiding theoretical perspectives and empirical findings from research examining the relationships between institutional predictors and these outcomes, mainly with respect to STEM fields but also considering broader higher education literature where STEM research is more limited. First, though, a brief overview of traditional approaches to STEM higher education research is provided.

An Orientation to Research on Science and Engineering Postsecondary Education

Henderson, Finkelstein, and Beach (2010) identify three distinct communities involved in research on teaching and learning in science and engineering postsecondary education: faculty development, discipline-based, and [STEM] higher education researchers. These communities operate in relative isolation and employ distinct lenses and research methods. Faculty development and discipline-based research is mainly concerned with pedagogy within specific disciplines and rarely includes multiple institutions, theoretical underpinnings, or analyses targeting underrepresented students. Borrego's (2007a) analysis of 700 engineering education publications found that just 7% were published in refereed journals, 4% "mentioned theory from the literature…or reported on statistical data analysis," and 4% focused on women or minorities (p. 13). On the other hand, STEM higher education research more often examines issues beyond pedagogy, is grounded in relevant social science theories, and explicitly considers underrepresented student outcomes. However, STEM higher education research typically neglects disciplinary heterogeneity and instead operationalizes STEM as arbitrary assortments of natural, social, behavioral sciences and/or engineering.

Both discipline-based (i.e., engineering education) research and STEM higher education research have traditionally emphasized student-level predictors. To the extent that engineering education research has examined persistence and completion, it underscores such influences as high school preparation and course-taking patterns, student attitudes, personality traits, demographics, and choice of engineering discipline (Adelman, 1998; Felder, Mohr, Dietz, & Baker-Ward, 1994; Felder, Felder, & Dietz, 2002; Ohland et al., 2008; Ohland & Zhang, 2002). Higher education research concludes that pre-college academic preparation and achievement explain the vast majority of variance between students in STEM persistence and degree completion (for example, Elliot et al., 1996; Smyth & McArdle, 2004; Fleming & Morning, 1998; Huang, Taddese, & Walter, 2000). Minority underrepresentation in STEM is also widely attributed to lower levels of self-efficacy, cultural congruity, ambition, or commitment to STEM (e.g., Leslie, McClure, & Oaxaca, 1998; Seymour & Hewitt, 1997; Gloria and Kurpius, 2001; Grandy, 1998; Hackett, Betz, Casas, and Rocha-Singh, 1992; Huang, Taddese, Walter, and Peng, 2000; Jackson, Gardner, and Sullivan, 1993).

While Eagan (2010) notes that institutional forces are neglected in STEM higher education research, he and other like-minded scholars have begun to address this gap in the knowledge through various studies of how institutional structures and contexts shape URM outcomes in STEM (for example, Malcom, 2008, 2010; Chang, Cerna, Hans, & Sàenz, 2008; Hurtado et al, 2009; Perna et al., 2009; Eagan, 2010; Hurtado, Newman, Tran, & Chang, 2010; Museus & Liverman, 2010; Hubbard & Stage, 2010; Newman, 2011a; Ong, Wright, Espinosa, & Orfield, 2011; Ostreko, 2012). This emergent literature greatly informs the present study.

Theoretical Perspectives Used to Examine STEM Retention, Completion, or Degree Production

Research examining how institutional factors contribute to educational outcomes in science and engineering draws on multiple theoretical frameworks, which are shaped by diverse disciplinary perspectives. In general, this research typically falls into one (or more) of three theoretical camps: interactionalist, organizational, and/or production functions.

Interactionalist frameworks. Research focused on retention and degree completion in STEM draws largely on interactionalist frameworks (Astin, 1975, 1984, 1993; Bean, 1980; Tinto, 1975, 1987, 1993) that emphasize (to varying degrees) the influence of academic and social integration on students' progress through college. In addition to the disputed applicability of these perspectives to underrepresented minority students (Cabrera, Nora & Castaneda, 1993; Flowers, 2004; Guiffrida, 2006; Hurtado & Carter, 1996; Nora, 2001; Terenzini et al., 1994; Tierney, 1999; Torres, 2003) or to non-traditional institutional contexts like HBCUs (Pascarella & Terenzini, 1991; Metz, 2004; Tinto, 2006), interactionalist perspectives have limited use for informing institutional efforts to improve retention (Berger & Braxton, 1998; Berger & Milem, 2000; Titus, 2004; Tinto & Pusser, 2006).

Indeed, Tinto and Pusser (2006) note that that while we have "made substantial progress in our understanding of the process of student persistence" to the extent that we "now know the broad dimensions of the process of student leaving...we are still unable to tell institutions what to do to help students stay and persist" (p. 2). While some scholars have offered more comprehensive frameworks with clearer implications for institutions (Braxton, Hirschy, & McClendon, 2004; Kuh et al., 2006; Tinto & Pusser, 2006; Swail, Redd, & Perna, 2003), as Titus (2004) observes, the role of institutional contexts has not yet been systematically explored in the research on retention/graduation. The absence of systematic consideration of the role of institutional context is also reflected in the prevalence of single-institution retention studies, which inherently offer no information about whether institutional contexts explain variations – between institutions – in institutional outcomes (Titus, 2004).

Organizational frameworks. Though virtually absent in the STEM higher education literature, organizational perspectives are recognized – though underutilized – in the broader higher education literature as more appropriate than internationalist theories for understanding the role of institutional characteristics and contexts in student persistence/completion (Tinto, 1993, 2006; Titus, 2004, 2006a, 2006b). Two often cited organizational frameworks are Bean's (1980, 1981) student attrition model and Berger and Milem's (2000) college impact model.

Bean's (1980, 1981) student attrition model marries the interactionalist concepts of academic and social integration and institutional commitment with concepts from worker turnover drawn from Price (1977), positing that organizational variables that can be "administratively manipulated" also influence student retention. Organizational variables include peer and faculty contact, organization memberships, support services. Bean (1981) notes that the model is designed for student-level, single institution analyses rather than comparisons between institutions; therefore, structural characteristics of institutions are excluded.

Berger and Milem's (2000) college impact model combines organizational theory and empirical research on student involvement and peer group effects to postulate that institutional and student characteristics influence such student outcomes as persistence and completion. Specifically, the Berger and Milem model suggests that student entry characteristics (e.g., gender, race/ethnicity, socioeconomic status, academic achievement); institutional characteristics (e.g., size, control, selectivity, location, Carnegie classification); institutional behaviors (e.g., resource allocation strategy); and student peer climate (e.g., aggregate student characteristics) influence student outcomes.

Higher education production functions. Production functions are rooted in microeconomic theory of the firm, specifically producer theory. To produce something requires taking inputs and using some process or technology to transform them into outputs. For example, a firm's workers might use chemicals and equipment to produce a vaccine. In this case, the workers, chemicals, and equipment are the inputs; and the process by which these inputs come together to produce the output, a vaccine, can be represented mathematically by a production function. In fact, a production function represents the process by which a firm generates the *maximum* output possible from a given mix of labor and capital inputs (Hanushek, 1979). Thus, production functions provide a basis for describing efficient production and determining appropriate responses to changes in inputs or technology.

Scholars and observers acknowledge that the notion of colleges and universities as producers with an estimable production function is tenuous at best (Salerno, 2002). Precise specification of the higher education production function requires that we can identify and quantify all relevant inputs and outputs, gauge the quality of the inputs and outputs, and express the nature of the relationships between inputs and outputs in mathematical terms (Hopkins, 1990). Whereas the vaccine manufacturer can directly measure the inputs and outputs of production and use engineering and scientific knowledge of the process to specify the production function, the higher education production process is essentially a black box. Reviewing thirty-two higher education production function studies, Hopkins (1990) concluded:

> It would be well to observe that no researcher to date has successfully characterized the [higher education] production function…and it is doubtful whether anyone ever will. The reasons for this are many, but they all boil down to the fact that the technologies of instruction, research, and public service are poorly understood, and the tools for estimating the requisite functional forms and coefficients are woefully inadequate to the task. To be more specific, not only are we lacking appropriate measures

> of quality, but the very nature of the interactions between, for example, teaching and research is difficult to express in mathematical terms. (p. 12)

But even though efforts undertaken to estimate the true and complete higher education production function might be hopeless, the production function can still be a useful lens for examining educational outcomes.

In fact, education production functions have provided a basis for studies of the impact of school resources on educational outcomes at the K-12 level dating back to the Coleman Report (Coleman et al., 1966). Harris (2010) makes the case that any study of the quantitative relationship between education inputs and outputs falls under the education production function (EPF) umbrella, whether or not the models estimated adhere strictly to the textbook tenets of production functions. Findings from EPF studies in K-12 are frequently used to inform policy debates and EPF methodologies are increasingly common in educational program evaluation (Harris, 2010).

In the higher education context, production functions – along with closely related cost functions – are common in research on European, Australian, and Canadian institutions (see Salerno [2003] and Eagan [2010] for a review). However, recent research explicitly drawing on producer theory to analyze American higher education is limited (some examples include: Dolan & Schmidt, 1994; Wolf-Wendel, Baker, & Morphew, 2000; Salerno, 2002; Blose, Porter, and Kokkelenberg, 2006; Titus & Eagan, 2008; Titus, 2009; Eagan, 2010; Ostreko, 2012). And fewer higher education production function studies examine STEM educational outputs (these studies include: Wolf-Wendel, Baker, & Morphew, 2000; Eagan, 2010; Ostreko, 2012).

Known Institutional Predictors of STEM Persistence, Completion, or Degree Production

The present study estimates an engineering bachelor's degree production function in which degree production is modeled as a function of institutional inputs, institutional characteristics, and aggregate student inputs. Consistent with this framework, this section of the literature review synthesizes what has been learned about the influence of these predictors on educational outcomes in STEM or in higher education (where the STEM literature is more limited). Specifically, institutional inputs include programmatic interventions, faculty factors, and institutional expenditures. Institutional characteristics include institutional control, Carnegie classification, selectivity, and HBCU status. Aggregate student characteristics include pre-college academic preparation, racial/ethnic diversity, and socioeconomic status. First, though, selected findings from pertinent qualitative research are presented.

Selected qualitative findings. Qualitative research suggests that how underrepresented minority students experience the culture(s) of science and interactions with faculty and peers may be at the heart of their persistence processes in science and engineering. Therefore, understanding the dynamics of these experiences might be critical to institutional and policy efforts to support URM students' STEM ambitions. These qualitative insights also offer directions for future research and color in the details of a picture that broader quantitative studies can only outline at best.

Cultures of science. Higher education researchers have devoted a great deal of attention to the ways that campus cultures, campus climates, and students' perceptions thereof, influence minority student outcomes (for example, Cabrera et al., 1999; Harper and Hurtado, 2007). But STEM disciplinary cultures and academic climates may present unique academic and social obstacles for underrepresented minority students (Hurtado, Cabrera, Lin, Arellano, & Espinosa, 2009; Johnson, 2007).

The "culture of science" presupposes a worldview meant to reflect the nature of science itself. Investigating how the culture of science contributes to the underrepresentation of women and minorities in a critical ethnography of working scientists and engineers, Jones (1998) put it this way:

> Scientists believe they can remove subjectivity from their treatment of people because they are convinced they can do this in their empirical work…The oppressive nature of the situation conceals itself in the sciences because of the aura of objectivity and premise of value-neutral activities that are supposed to be part of the scientific method. (p. 8)

Students' assimilation to the culture of science is a major thrust of STEM higher education that Seymour and Hewitt (1997) likened to induction into a fraternity. Igbarra (1999) suggests that URM students may have more difficulty navigating perceived distances between their cultures of origin and the culture of science – the greater the distance the more diminished are students' prospects for persistence (Kuh & Love, 2000). In another ethnographic study, Johnson (2007) found that URM women grappled with:

> a sense of being conspicuous, a hesitancy to draw attention to themselves, a conflict between the altruistic reasons that have drawn them to the study of science and their professors' valuing science in and of itself, interpretation of professors' narrow focus on science as hostility and lack of caring, and skepticism regarding science's claim to be neutral to race, ethnicity, and gender… (p. 818)

Underrepresented minority STEM students are also disproportionately weeded out of gatekeeper courses and report difficulty adjusting to pedagogical practices like grading on a curve that foster competitive climates (Seymour & Hewitt, 1997; Johnson, 2007; Hurtado et al., 2009; Fries-Britt, Younger, & Hall, 2010). (Gatekeeper or "weed-out" classes are usually taken during the first or second year of college, and success or failure often dictates whether students persist in their STEM major. For example, engineering gatekeeper courses include calculus, physics, statics, etc.) URM students often report facing stereotypes and assumptions of academic inferiority and feeling burdened to "prove" themselves in order to be accepted into the community of science (Moore, Madison-Colmore, & Smith, 2003; Fries-Britt, Younger & Hall, 2010). Exploring the perceptions, attitudes, and experiences of 24 African American male juniors and senior engineering majors at a large, southeastern predominantly White institution, Moore, Madison-Colmore, and Smith (2003) coined the term "prove-them-wrong syndrome" to explain their persistence in engineering. That is, the students in the study were driven to persist in engineering by a desire to prove faculty, peers, society, or anyone they perceived as doubting their academic potential wrong. Yet not all students are able to turn negative perceptions or interactions into a source of motivation to achieve. Kuh and Love (2000) suggest that institutions can moderate the negative influences of STEM cultures and disciplinary climates by creating opportunities for students to form positive sociocultural connections with faculty and peers.

Interactions with faculty. In a qualitative study of 73 undergraduate STEM students at two institutions, Thiry and Larsen (2011) found that more so than other students, URMs gained confidence and broadened their perspectives on career and educational options as a result of positive contact with faculty. Others have also linked interactions with faculty to minority students' self-efficacy, achievement, and career expectations (Santiago & Einarson, 1998; Carter 2002; Cole & Espinoza, 2008) and suggested that positive outcomes are more pronounced when students interact with same-race faculty (Fries-Britt, 1998; Fries-Britt, Younger, & Hall, 2010; Griffin, Perez, Holmes, & Mayo, 2010). In Seymour and Hewitt's (1997) landmark study, STEM defectors of color frequently cited unapproachable, intimidating faculty along with their experiences in gatekeeper courses as instrumental in their departure decisions. Experiences with faculty outside the classroom are also important. Exploring the laboratory experiences of twenty-four students of color, Malone and Barabino (2009) concluded that rather than helping to develop their identity as researchers or scientists, laboratory experiences often involved ambiguous and subtly racial interactions with faculty and peers and feelings of isolation and disillusionment.

Interactions with peers. Like interactions with faculty, research highlights the importance of peer interactions in shaping minority students' experiences in STEM. For example, high-achieving URM physics majors described peers as their "saving grace," particularly given the intensity of their programs and limited time to develop relationships outside their academic bubbles (Fries-Brit, Turner, & Hall, 2010). Another study indicated that same-race peer interactions supported Black STEM students' academic and racial identity development and diminished feelings of isolation (Fries-Britt, 1998). Willemsen (1995) also found that positive peer interactions diminished isolation, boosted learning in weed-out courses, and helped students feel less different and distant from their classmates. These studies illustrate an emphasis in the literature on gains associated with same-major (e.g., Astin & Astin, 1992) and same-race (e.g., Grandy, 1998) peer interactions. Other studies suggest that engagement with non-STEM peers takes away from the time needed to meet the demands of STEM majors and marginalizes URMs from their respective STEM cultures (Bonous-Hammarth, 2000; Museus, Palmer, Davis, & Maramba, 2011; Cole & Espinoza, 2008).

Summary of selected qualitative findings. Qualitative research offers a window into underrepresented students' STEM experiences, emphasizing the critical role of culture, faculty and peers. However, results from these qualitative studies are not necessarily generalizable to URMs in STEM broadly or to specific racial/ethnic groups in specific STEM disciplines. Nevertheless, institutional inputs, which are discussed in the next section, reflect institutional and public policy efforts to put this knowledge into practice by creating conditions to facilitate students' assimilation to the cultures of science and foster positive interactions with faculty and peers.

Institutional inputs. Production functions typically specify a firm's inputs in terms of capital and labor. Research suggests that faculty are colleges and universities' most important labor input because they are central in the production of all three outputs of higher education – instruction, research, and service (Salerno, 2002; Lewis & Dundar, 2001). Accordingly, proxy measures of faculty (labor) inputs – instructional expenditures, faculty salaries, or other faculty characteristics, for example – are almost universally included in higher education production function studies. Production studies examining the instructional outputs of higher education (like degrees) occasionally account for student "labor" inputs or characteristics (e.g., Webber & Ehrenberg, 2010; Webber, 2012). Purely capital inputs (for example, buildings, equipment, land, etc.), on the other hand, are less frequently specified in multi-institution studies for at least two reasons. Differences in accounting practices across institutions make obtaining consistent measures of institutional capital difficult (Salerno, 2002). Also, institutional capital is not viewed as a realistic policy lever, since unlike faculty labor inputs over which institutions have a fair amount of discretion by assigning teaching loads, granting release time for research, or varying levels of adjunct and teaching assistant labor inputs, the majority of institutional capital is relatively fixed over time in land, buildings, equipment (Salerno, 2002). Salerno (2002, 2003) reviews the tradeoffs involved with specifying labor and capital inputs in higher education production studies.

This section of the review synthesizes what is known about the role of institutional inputs in the production of STEM higher education outputs. Specifically, the inputs identified include programmatic interventions, faculty predictors, and institutional expenditures.

Programmatic interventions. Formal programs seem to be the cornerstone of institutional efforts to expand success in science and engineering for underrepresented minorities. Yet despite their prevalence, little is known about the effects of various STEM programs on student outcomes (see Urban Institute [2005] for a comprehensive review of "effective" STEM programs). Nevertheless, colleges and universities routinely operate and/or support programs designed to foster collaborative learning environments and facilitate positive interactions with faculty and peers – such as minority freshmen orientation, clustering, and structured study groups (Reichert & Absher, 1997); peer mentoring programs (Astin & Astin, 1992; Good, Haplin, & Haplin, 2000); and student-chapter professional organizations (Jackson, Gardner, & Sullivan, 1993; Reichert & Absher, 1997; Chang, Cerna, Han, & Saenz, 2008; Hurtado et al., 2007). However, the most frequently studied systemized efforts to improve URM outcomes in STEM seem to be summer bridge, undergraduate research, and comprehensive retention programs.

Summer bridge programs. STEM summer bridge programs are pre-college programs that facilitate accepted students' academic and social transition from high school to college. These programs are often designed to 1) promote students' interest in STEM and academic self-efficacy and 2) orient students to college life and the academic unit's culture through intensive, structured academic and residential experiences (Evans, 1999; Urban Institute, 2005; Pascarella & Terenzini, 2005). In the process, students are thought to develop skills, career goals, and relationships, which are expected to mediate their subsequent persistence and eventual degree attainment in STEM.

To a limited extent, research supports this premise. For example, Evans (1999) found that participants in a six-week community college summer bridge program targeting minorities in STEM had comparable or higher academic performance, first-year persistence, and graduation rates relative to non-participants. Walpole and colleagues (2008) analyzed longitudinal survey data and administrative records to show that summer bridge participants' three-year persistence rates exceeded those of the control group. A similar observational study found that participants in an engineering summer bridge program were 25% more likely to persist and graduate in engineering than non-participants with similar high school GPAs (Ohland & Zhang, 2002). Many others have attributed positive STEM outcomes to summer bridge programs based on less rigorous (i.e., no control/comparison group) evaluation methods (Ami, 2001; Zhe, Doverspike, Zhao, Lam, & Menzemer, 2010). Yet by and large, Perna's (2003) conclusion remains true today: despite widespread acceptance and appeal there is an absence of strong empirical evidence of the effectiveness of [STEM] summer bridge programs.

Undergraduate research. Relative to summer bridge, the literature on STEM undergraduate research programs is vast. This is not surprising given the long history of undergraduate research in the sciences – liberal arts colleges have engaged undergraduates in research on a broad scale since at least the 1940s (Laursen et al., 2010). Federal support for STEM undergraduate research appears to date back to 1958 when the National Science Foundation (NSF) established the Undergraduate Research Program (National Science Foundation, 2008). In fiscal year 2006, at least 11 federally funded STEM education programs expressly included undergraduate research, with NSF sponsoring seven of these programs to the tune of $116 million (Department of Education, 2007). Federal dollars also support STEM undergraduate research indirectly through funding for infrastructure improvements to sustain research initiatives involving undergraduates. And private funders make substantial investments in STEM undergraduate research through a variety of programs (Laursen et al., 2010).

The STEM education movement advances research as a viable strategy for increasing persistence in STEM and expanding participation of traditionally underrepresented groups (Carter, Mandell, & Maton, 2009; Barlow & Villarejo, 2004; Hurtado, et al., 2008). And participation in undergraduate research appears to be widespread. Russell (2006) estimated that 53% of STEM undergraduates participate in some form of research, based on data from a nationally representative sample of 22- to 35-year-old STEM bachelor's degree-holders. Other research indicates that there are not enough research opportunities to accommodate interested students (Laursen et al., 2010).

Undergraduate research programs are generally structured to include mentoring, training in laboratory techniques, and formal presentation of results (Laursen et al., 2010). A broad range of benefits have been linked to undergraduate research: from increased technical knowledge, laboratory, problem-solving, and presentation skills to clarification of career and post-baccalaureate educational plans (Kardash, 2000; Lopatto, 2004, 2007; Laursen et al., 2010). Concerning underrepresented STEM students, undergraduate research reportedly increases academic performance, self-efficacy, undergraduate persistence, and graduate school enrollment (Barlow & Villarejo, 2004; Carter, Mandell, & Maton, 2009; Hurtado et al., 2007; Lopatto, 2004; Nagda et al., 1998).

Though they attribute a range of positive effects to undergraduate research, scholars and evaluators also acknowledge the lack rigorous empirical evidence to support these claims (Laursen et al., 2010; Lopatto, 2007; Carter, Mandell, & Maton, 2009). The 1998 evaluation of the University of Michigan's Undergraduate Research Opportunity Program (UROP) remains the one and only randomized controlled trial[2] of a STEM

[2] There are a number of explanations for the absence of RCTs or quasi-experimental designs with well-matched comparison groups in the evaluation literature on STEM undergraduate research programs. Random assignment of subjects to participate (or not participate) in undergraduate research is often infeasible (Kardash, 2000; Lopatto, 2007; Bauer & Bennett, 2003). Also, RCTs and quasi-experiments with sample sizes large enough to obtain findings with statistical significance can be considerably more costly and difficult to execute than, for example, one-group pre-post studies. And the literature suggests that efforts to assess the impact of undergraduate research programs almost always begin after (in some

undergraduate research program (Nagda, Gregerman, Jonides, von Hippel, & Lerner, 1998). A large applicant pool and a limited number of spaces allowed University of Michigan evaluators to use a stratified random sampling method to select students for participation in the program. Administrative records revealed that, compared to control, UROP participation improved persistence (in college) for African Americans at all enrollment levels and for Whites and Hispanics who participated as sophomores. The program had the strongest positive effects for African Americans with GPAs below the median for their racial/ethnic group (Nagda et al., 1998).

Although a number of other studies offer rich insights about the relationship between participation in undergraduate research and student outcomes in STEM, no causal links can be drawn from this research due to several methodological limitations. Chief among these limitations are measurement and selection problems. For example, only a few observational studies examine the relationship between undergraduate research and *direct* outcome measures like GPA or persistence in major (for example, by analyzing administrative records as in Barlow, & Villarejo, 2004; Jones, Barlow, & Villarejo, 2010; and Carter, Mandell, & Maton, 2009). However, most evaluation studies of STEM undergraduate research programs use self-report outcome measures based on participant ratings on items like: understand the research process; learned *x-y-z* specific research skills, gained self-confidence, expect to earn a Ph.D., or interested in research career. These self-reports are helpful for assessing learning and experience outcomes that

---

cases many years after) the intervention is already underway – or once the opportunity to assign or thoughtfully construct groups has passed.

may be associated with the research program, but they fall short of pinpointing program effects (Kardash, 2000; Lopatto, 2007). Another measurement issue that undermines the validity of STEM undergraduate research program evaluations is that other than a few studies (i.e., Lopatto, 2004, 2007; Bauer & Bennett, 2003; Zydney, Bennett, Shahid, & Bauer, 2002) the data used to assess program impact is drawn from surveys of participants who knew their responses would be used for evaluative purposes. Also, students who apply or sign up for undergraduate research programs are likely to be more motivated to persist in STEM than students who do not, raising concerns about potential selection biases.

Twelve years ago, an NSF program manager told *Science Magazine*, “As an assumption, undergraduate research makes logical sense. But we have no idea what students actually learn from it” (Mervis, 2001, p. 1614). Certainly, available research has contributed greatly to our understanding of how undergraduate research experiences might foster persistence and degree attainment for STEM students by fostering their academic and social engagement and increasing their self-efficacy. However, there remains a need for stronger empirical evidence of their potential impacts.

Comprehensive retention programs. Legions of institutions have implemented comprehensive programs that integrate multiple interventions to foster success for underrepresented minority science and engineering students (Good, Haplin, & Haplin, 2002; Committee on Equal Opportunities in Science and Engineering, 2004; Urban Institute, 2005; May & Chubin, 2003; Museus, Palmer, Davis, & Maramba, 2011). But similar to summer bridge and undergraduate research programs, evidence of the effectiveness of these efforts is limited. Still, two well-regarded program models have been widely replicated and are frequently held up as exemplars of the programmatic approach: The Meyerhoff Scholars Program, and the Minority Engineering Program.

Established in 1988, the Meyerhoff Scholars Program incorporates a number strategies intended to foster student success in science and engineering: a four-year financial aid package, a mandatory summer bridge program, study groups, personal and academic counseling, tutoring, summer research internships, community service, and mentoring (Maton, Hrabowski, & Schmitt, 2000). Although initially targeted to African American males, the program has since expanded to include all high-achieving students "interested in the advancement of minorities in the sciences and related fields" (University of Maryland, 2012).

Numerous quantitative and qualitative studies have examined the effects of the Meyerhoff Scholars Program (Hrabowski & Maton, 1995; Maton, Hrabowski, Schmitt, 2000; Maton & Hrabowski, 2004; Summers & Hrabowski, 2006; Carter, Mandell, & Maton, 2009; Fries-Britt, 1998). The earliest published evaluation of the program compared the performance of the first three Meyerhoff cohorts (*N* = 69) to a matched pre-Meyerhoff historical comparison group of Black students with comparable SAT scores and high school GPAs. On average, Meyerhoff scholars' overall GPA (*Mean* = 3.5) was significantly higher than that of comparison group students (*Mean* = 2.8), as were Meyerhoff grades in gatekeeper course (Hrabowski & Maton, 1995). A subsequent study of the longer-term impacts of the program found that Meyerhoff students were more likely to persist and graduate in STEM, earned higher GPAs, and enrolled in STEM graduate programs at higher rates than multiple comparison groups (Maton, Hrabowski, & Schmitt, 2000). Other studies highlight the rate of STEM doctoral degree attainment among Meyerhoff alumni (Maton & Hrabowski, 2004), the effects of the summer research internship (Carter, Mandell, & Maton, 2009), participant experiences (Fries-Britt, 1997, 1998), and the broader implications of the program (Hrabowski, 2002).

The original Minority Engineering Program (MEP) was initiated by faculty at California State University, Northridge, in 1973 to improve minority retention and performance in engineering. The MEP model has since been replicated at more than 100 universities and privately operated programs (May and Chubin, 2003). Though implementation of the MEP model varies, key elements include: a formal freshmen orientation course, clustering of underrepresented students in common course sections, a student study center, and structured study groups. To a lesser extent, MEP programs also include pre-college outreach, summer bridge, scholarships, supplemental instruction, professional development activities, advising, undergraduate research, and assessment tools (May & Chubin, 2003; Tsui, 2007). May and Chubin (2003) note that essential to the success of the MEP model in operation is a focus on the academic rather than "student services" aspects of the program.

Evaluations of the MEP model at several institutions generally indicate significant gains in achievement and persistence for minority engineering students. One early impact study reported that URM participants at the University of California and California State University campuses persisted at higher rates than all other engineering students and three times the rate of non-MEP minorities (Landis, 1988). On average, Berkeley MEP participants earned a letter grade higher in science and mathematics courses than non-MEP minority students and also achieved higher grades than White students in those courses (Treisman, 1985). In a more recent study, Ohland and Zhang (2002) found that while MEP students at the Florida A&M University-Florida State University College of Engineering persisted at higher rates than non-participants, this difference was statistically non-significant after controlling for high school GPA. On the other hand, examining the long-term program effects for Black engineering majors who participated in a freshman-oriented MEP, Good and colleagues (2002) detected no differences in sophomore GPA. In another study, African American MEP participants had significantly higher sophomore persistence rates (76%) than non-participants (38%) (Good, Haplin, & Haplin, 2002). These inconsistent findings from single institution studies no doubt point to widespread variations in program implementation.

Summary of institutional programmatic interventions. Programmatic interventions such as summer bridge, undergraduate research, and comprehensive retention and support programs represent key institutional inputs that appear to influence persistence and degree completion in science and engineering for underrepresented minorities. Available empirical research is largely suggestive of positive effects on a range of student outcomes but provides little conclusive evidence. Moreover, wide variability between institutions in the implementation of ostensibly similar programs limits the potential for systematic, multisite evaluations or meta-analyses of STEM programmatic efforts. Variability between institutions in the role or salience of institutional agents in the operation of programs or as direct contributors to student outcomes presents another potential confounder to systematic analyses. And perhaps most important, the extent to which consistent measures of STEM programmatic inputs can be developed across institutions is questionable at best. Yet there is still a pressing need to at least estimate the relationships between these institutional inputs and STEM educational outputs.

Faculty predictors. As noted, qualitative research examining underrepresented minority student outcomes in STEM often underscores how interactions with faculty shape students' experiences, attitudes, and persistence processes (for example, Perna et al., 2009; Fries-Brit, Younger, and Hall, 2010). Yet only a few quantitative studies have examined the relationship between faculty-focused measures and URM outcomes in STEM. In fact, faculty measures have been largely neglected as potential predictors of educational outcomes in the broader higher education empirical literature as well (Chen, 2012; Ehrenberg & Zang, 2005). Most of the available research in this area operationalizes faculty predictors in terms of: the proportions of part-time faculty or graduate student teaching assistants relative to tenured and tenure-track faculty (Bettinger & Long, 2004, 2006; Schibik & Harringon, 2004; Ehrenberg & Zhang, 2005; Eagan, 2010; Hubbard & Stage, 2010; Chen, 2012; Ostreko, 2012); faculty-student ratios (Dolan & Schmidt, 1994; Sibulkin & Butler, 2011; Chen 2012); faculty racial composition (Griffith, 2010; Hubbard & Stage, 2010; Price, 2010; Ostreko, 2012); or faculty gender composition (Griffith, 2010; Ostreko, 2012). Collectively, this research indicates that faculty inputs matter for retention, graduation, and degree production in higher education in general and in science and engineering specifically.

As one of the most prominent trends in higher education, the growing reliance on part-time or adjunct instructors has prompted a number of scholars to examine the implications for educational outcomes in recent years (Bettinger & Long, 2004). Available research generally indicates that exposure to instructors outside the full-time, Ph.D.-trained traditional model is associated with worse outcomes for students, with differential effects noted across institutional control, Carnegie classification, academic disciplines, and student race/ethnicity.

Bettinger and Long (2004, 2006) estimated the effects of adjuncts and graduate student teaching assistants on students' subsequent course-taking patterns, major choice, and persistence, drawing on administrative data from four-year public institutions in the state of Ohio. The latter study produced OLS and instrumental variables estimates of the effects of exposure to non-traditional instructors in the first semester on first-year dropout. Both exposure to adjuncts and exposure to teaching assistants increased the likelihood of dropout (Bettinger & Long, 2006). The earlier study used fixed effects regression models to analyze course-taking and major choice by subject (Bettinger & Long, 2004). For the pooled sample of first-time, full-time students across all subjects, exposure to adjuncts and exposure to teaching assistants in the first semester reduced the number of subsequent credit hours taken in the subject and reduced the likelihood of majoring in the subject. Yet, perhaps more interesting, these effects varied by academic disciplines, even specifically within STEM. Whereas exposure to adjuncts in first semester biology, chemistry, physics and computer science courses reduced subsequent course taking and major selection in those subjects, adjuncts had no statistical relationship with engineering students' outcomes. On the other hand, exposure to teaching assistants in biology, chemistry, and physics reduced students' subsequent course taking in those subjects but was not related to course taking in computer science or engineering. Exposure to teaching assistants in biology, physics, and engineering reduced the likelihood of selecting those subjects as majors, but was not statistically related for chemistry and computer science.

Using administrative data on freshmen drawn from a single institution, Schibik & Harrington (2004) found that exposure to part-time faculty reduced the likelihood of persistence to the second semester. Chen's (2012) multi-level event history analysis found no relationship between part-time faculty and student dropout. However, unlike the other student-level analyses, Chen (2012) modeled 6-year dropout and relied on assumptions about the extent of students' exposure to part-time instructors rather that data directly linking students to instructors. Ehrenberg and Zhang (2005) used institution-level panel data from the College Board and IPEDS and fixed effects regression models, finding that the proportion of part-time faculty and the proportion of full-time, non-tenure track faculty were negatively related to graduation rates. The magnitude of the estimates varied by institutional control and Carnegie classification, being greatest at public master's institutions. In the same vein, Eagan (2010) found that the proportion of part-time faculty (institution-wide) reduced institutions' STEM degree production rate. Hubbard and Stage (2010) found that the share of tenure-track faculty was not related to alumni STEM doctoral degree productivity for underrepresented minorities, but given data limitations their "tenure ratio" was only a crude approximation of what students' may have experienced as undergraduates. And, conceptually, Ostreko's (2012) finding of no relationship between the proportion of tenure track faculty and engineering graduate degree production for underrepresented minorities seems reasonable since graduate students (especially Ph.D. students) should have less exposure to part-time instructors than lower-division undergraduates (Bettinger and Long, 2006). Thus, the generally negative effects of exposure to non-traditional faculty are most pronounced at the undergraduate level, vary across academic disciplines, and are best detected with data that clearly links students and instructors.

Faculty-student ratio has been linked with higher shares of alumni earning doctoral degrees for students in all fields (Dolan & Schmidt, 1994; Sibulkin & Butler, 2011) but has been reported to be unrelated to alumni doctoral degree attainment for African Americans in STEM fields (Sibulkin & Butler, 2011). Ehrenberg and Zhang (2005) found that the number of faculty was positively related to institutional graduation rates, but Chen (2012) found no relationship between faculty-student ratio and undergraduate persistence. Overall, different outcomes, data, and analysis methods make it difficult to square these findings and suggest a need for further research.

Available research indicates that faculty demographic characteristics may also be related to educational outcomes in STEM fields. Price (2010) analyzed administrative records from public institutions in Ohio to generate instrumental variables estimates of the effects of exposure to Black instructors on first-semester and first-year persistence in STEM. He found that exposure to Black instructors was not significantly related to outcomes for non-Black students but was positively related to Black students' persistence in STEM. In the same spirit, the proportion of underrepresented minority faculty (institution-wide) was associated with higher shares of URM alumni earning STEM doctoral degrees (Hubbard & Stage, 2010). Alternatively, Griffith (2010) reported that the proportion of female faculty (institution-wide) was negatively related to fist-year persistence but unrelated to fourth-year persistence in STEM for women, men, and non-minorities. The proportion of female faculty was also unrelated to any minority student outcomes. However, Griffith did not control for faculty rank, which could potentially confound the results since women are more likely to hold lower rank positions in STEM (Nelson & Rogers, 2007). In fact, Ostreko (2012) found that the percentage of female tenured/tenure-track faculty was positively related to graduate degree production for women in engineering.

The influence of other faculty-centered measures on educational outcomes has also been examined. Dolan and Schmidt (1994) reported that an institution's average salary for associate professors was associated with higher shares of alumni earning doctorate degrees. And Hurtado, Eagan, and Hughes (2012) found that the proportion of faculty involving undergraduates in research predicted student persistence in STEM fields. Hurtado and colleagues (2012) used hierarchical generalized linear modeling to analyze student- and institution-level data from a variety of sources, including the CIRP Faculty Survey. They actually tested two other faculty predictors – the proportion of faculty grading on a curve and a measure of the extent of student-centered pedagogy – but found no significant relationship with STEM persistence.

Summary of faculty predictors. Exposure to part-time faculty is the most frequently studied measure in research examining relationships between faculty characteristics and educational outcomes. By and large, this research associates adjuncts, teaching assistants, and other non-tenure track instructors with worse educational outcomes. But differential effects are noted across institutional control, Carnegie classification, academic disciplines, and student race/ethnicity. Some evidence suggests that faculty-student ratios may matter for educational outcomes. And faculty race and gender have been significant predictors of various indicators of success for underrepresented students in STEM fields.

Institutional expenditures. At least one study measured the influence of faculty on underrepresented minorities' STEM outcomes from another angle. Griffith (2010) postulated that higher ratios of research to instructional expenditures reflected a greater institutional commitment to research relative to teaching, thus diminished opportunities for faculty-student interaction. Her OLS estimates suggested differential relationships by STEM outcome measure (i.e., persistence vs. degree completion) and undergraduate enrollment level. Currently, however, there is no conceptual framework that spells out the mechanism(s) by which institutional expenditures might influence educational outcomes – regardless of academic discipline – even though a growing literature specifically examines these relationships (Ryan, 2004). And a preponderance of contradictory findings from this research stymies efforts to develop such a framework.

Nonetheless, Salerno (2002) and Lewis and Dundar (2001) suggest that instructional expenditures, of which faculty salaries comprise a significant share, are good proxies for institutions' faculty inputs in a production framework. This notion could be easily extended to other expenditure categories to the extent that costs for student services and academic support services are associated with faculty and staff time and effort, again assuming capital inputs (e.g., land, buildings, equipment) are relatively fixed. Webber and Ehrenberg (2010) note that since we cannot directly measure the true inputs – time and effort – expenditures can be considered inputs multiplied by prices. Berger and Milem's (2000) college impact model also offers some support for conceptualizing spending as an "institutional behavior" that reflects the priorities of the institution and is indirectly related to student outcomes.

With few exceptions, empirical research that has considered links between various institutional expenditures and educational outcomes (i.e., retention, completion, degree production) indicates that expenditures generally matter. However, inconsistent findings about the degree to which different types of expenditures matter suggest that the relationships between these inputs and outputs are fairly complex. This section reviews recent studies that estimate the influence of institutional expenditures on educational outcomes for STEM students specifically and in higher education broadly.

Expenditures in STEM studies. A handful of studies examine the relationship between institutional expenditures and educational output, focusing specifically on underrepresented minorities in science and engineering. Collectively, the results of these studies are not easily reconcilable, since they reflect different outcome measures, academic disciplines, and expenditure categories.

Roper's (2011) descriptive study found that institutions in the lowest per student expenditure quintile were most likely to produce "very high" numbers of underrepresented minority STEM baccalaureates. However, without attempting to control for other institutional characteristics that could explain high numbers of URM baccalaureates (i.e., the racial composition of the student body), Roper's (2011) analysis is limited.

Griffith (2010) modeled first-year and fourth-year persistence in STEM separately for men, women, minorities and non-minorities using data from the Andrew Mellon Foundation's National Longitudinal Survey of Freshmen. She also modeled degree completion in STEM using the National Center for Educational Statistics' National Education Longitudinal Study of 1988. Controlling for student and institution characteristics, this study found that institutional research expenditures were negatively related to first-year persistence in STEM for URMs (and moderately so for non-URMs), but unrelated to fourth-year persistence for any students. In addition, research expenditures were unrelated to degree completion in STEM for URMs but positively related to completion in STEM for non-URMs (Griffith, 2010). Webber (2012) applied the production function in a competing risks regression framework to estimate the effects of institutional expenditures on six-year completion. Drawing from student-level administrative data from four-year public institutions in Ohio public colleges and universities, Webber divided his sample and found that instructional expenditures were more important for predicting completion for STEM majors compared to non-STEM majors.

Amanda Ostreko (2012) used institutional data from the American Society for Engineering Education's *Engineering College Profiles and Statistics* and OLS regression to examine predictors of graduate degree production, specifically in engineering. She reported an inverse relationship between engineering research expenditures and engineering doctorate degree production for URMs, but no significant relationship for engineering master's degree production, controlling for engineering school demographics. Wolf-Wendel, Baker, and Morphew's (2000) baccalaureate origin study found that instructional expenditures predicted alumni STEM doctoral degree productivity for White women but were not significant for Black and Latina women, controlling for structural and demographic characteristics of the baccalaureate institution. Hubbard and Stage (2010) also analyzed the baccalaureate origins STEM doctorate recipients. They reported a negative relationship between institutional funded research expenditures and alumni STEM doctoral degree productivity for underrepresented minorities but no significant relationship for instructional expenditures, controlling for institutional characteristics (Hubbard and Stage, 2010).

Expenditures in higher education persistence/completion studies. Although few STEM-focused studies consider institutional expenditures, they are increasingly examined in the broader higher education persistence/completion literature. The reason is summed up by higher education public policy expert, Jane Wellman (2010):

> American higher education is being challenged as never before by the imperative to increase postsecondary access and degree attainment despite declines in funding. The challenge is made all the more daunting because of rapid changes in student demographics. Meeting these challenges without harming quality will require unprecedented attention to the intersection of resource use and performance…Institutional and policy

> leaders are asking for guidance, and for data that tells them something about how to focus scarce resources in areas that make the biggest difference... (p. 3)

Wellman's (2010) challenge to researchers to "connect the dots" between spending and student success in higher education seems to have taken hold, as a number of recent studies examine the relationship between institutional expenditures and educational outcomes (for example, Webber & Ehrenberg, 2010; Webber, 2012; Chen, 2012; Peerenboom, 2012; Morrison, 2012). The studies identified for this review operationalize expenditures in terms of total (aggregate) expenditures, a single expenditure category (e.g., instructional expenditures), or multiple expenditure categories.

In regression models of institutional retention and graduation rates, total expenditures have consistently been associated with better outcomes, controlling for institutional demographic and structural characteristics (Goenner & Snaith, 2004; Porter, Blose, & Kokkelenberg, 2006; Morrison, 2012). Studies that operationalize institutional expenditures in terms of a single expenditure functional category have also found significant positive associations. Scott, Bailey, & Kienzl (2006) found that higher instructional expenditures predicted higher 6-year graduation rates using grouped logistic regression and controlling for institutional characteristics. Kim, Rhoades, and Woodard (2003) used hierarchical non-linear modeling and found a borderline positive association between funded research expenditures and 5-year graduation rates, controlling for student- and institution-level characteristics. Together, these studies confirm the importance of resource allocations. But aggregate expenditures do not tell us which types of expenditure categories actually make a difference. And singular conceptions of expenditures are limited since they that do not control for spending in other functional categories.

Moreover, studies that disaggregate expenditures into multiple functional categories have not reached consensus on the extent to which different expenditure categories influence educational outcomes. Research provides evidence of a positive relationship between retention/graduation/degree productivity and instructional expenditures (Ryan, 2004; Hamrick, Schuh, & Shelley, 2004; Scott, Bailey, & Kienzl, 2006; Webber & Ehrenberg, 2010; Webber, 2012); academic support expenditures (Dolan & Schmidt, 1994; Hamrick, Schuh, & Shelley, 2004; Ryan, 2004; Gansemer-Topf & Schuh, 2006); and expenditures for student support services (Webber & Ehrenberg, 2010; Chen, 2012; Webber, 2012). Other research contradicts these findings, suggesting no statistically significant relationship between retention/graduation and instructional expenditures (Chen, 2012; Titus, 2006a, 2006b, Peerenboom, 2012); academic support expenditures (Webber & Ehrenberg, 2010; Chen, 2012; Peerenboom, 2012; Webber, 2012); or expenditures for student support services (Ryan, 2004; Hamrick, Schuh, & Shelley, 2004). And at least one model produced a negative relationship between retention/graduation and instructional expenditures (Peerenboom, 2012).

Contradictory findings have also been reported concerning the role of funded research expenditures, with some research suggesting a negative association with graduation rates (Webber & Ehrenberg, 2010; Peerenboom, 2012) and others suggesting no significant relationship (Dolan & Schmidt, 1994; Titus, 2006a, 2006b). A few studies have also produced inconsistent findings concerning institutional support expenditures (Hamrick, Schuh, & Shelley, 2004; Ryan, 2004; Gansemer-Topf & Schuh, 2006; Titus, 2006a, 2006b; Peerenboom, 2012) and expenditures for grants and scholarships (Dolan & Schmidt, 1994; Titus 2006a, 2006b; Gansemer-Topf & Schuh, 2006; Peerenboom, 2012).

The lack of consistent findings between studies examining the links between expenditures and educational outcomes has been broadly attributed to data and methodological differences (Pike, Smart, Kuh, & Hayek, 2006; Webber & Ehrenberg, 2010; Morrison, 2012). Virtually all of the studies identified drew institutional expenditure data (for various fiscal years) from IPEDS and used basic regression models to analyze these data. Yet contradictory findings are reported both within and between studies for just about every expenditure category. Cleary, the relationships between institutional expenditures and educational outputs are complex. Perhaps the main aspect of complexity, which undoubtedly gives rise to inconsistent findings, is the challenge of comparing institutions based on institution-level finances. Reconciling expenditure data across diverse institutions is difficult both for researchers seeking to "connect the dots" along these lines and institution and policy leaders seeking practical guidance.

Why are institutional comparisons based on finances so difficult? Foremost, institutional finance data reported to the National Center for Education Statistics and published through IPEDS is simply not ideal for comparisons between institutions[3]

[3] Acknowledging the limitations of IPEDS finance data in raw form, Webber and Ehrenberg (2010) and Webber (2012) used data from the Delta Cost Project Database. The Delta Cost Project compiles, organizes, and edits IPEDS finance data to mitigate changes in financial reporting standards over time, impute missing data, and facilitate fairer institutional and longitudinal comparisons (Lenihan, 2012).

(Toutkoushian, 2001). Different reporting standards[4] for public and private institutions and other differences in accounting practices across institutions could result in different institutions assigning the same expenditure item to different IPEDS expenditure categories. Blose, Porter, and Kokkelenberg (2006) argued that mixing public and private institutions might confound the results of studies that compare funding levels across institutions. For example, Scott, Bailey, and Kienzl (2006) reported that they stratified their sample by institutional control after initial specifications tests of a pooled sample (which included a dummy variable for institutional control) indicated that the covariates in their graduation rate model functioned differently for public and private institutions. This evidence of variations by institutional control calls into question several of the studies identified in this review that combined public and private institutions (i.e., Goenner & Snaith, 2004; Ryan, 2004; Titus, 2006a, 2006b; Chen, 2012).

Institution-level finance data from IPEDS also masks important differences between institutions in academic mission. Some studies attempted to adjust for these potential differences by adding dummy variables to their models to control for Carnegie classification (for example, Hamrick, Schuh, & Shelley, 2004) or by restricting their sample(s) to institutions of similar Carnegie classes (for example, Ryan, 2004, Goenner & Smith; Gansemer-Topf & Schuh, 2006, and Morrison, 2012). However, a U.S. Department of Education report on the Delaware Study of Instructional Costs and Productivity found that, after adjusting for Carnegie classification, over 80% of the

[4] Public colleges and universities use the Governmental Accounting Standards Board (GASB) reporting format, while private institutions use the Financial Accounting Standards Board (FASB) reporting format.

variation in instructional costs across four-year colleges and universities is attributable to the mix of disciplines offered at the institutions (Middaugh, Graham, & Shahid, 2003).

Giving the example of two research/doctoral intensive universities – one heavily oriented toward natural and physical sciences and graduate education, the other focused on the social sciences and humanities and less so on graduate education – Middaugh and colleagues (2003) warned, "Any institution-wide comparison of costs without consideration of disciplines between these universities will be totally misleading." Blose, Porter, and Kokkelenberg (2006) offered an economic production perspective, noting that each discipline "requires different inputs and…often engages different technologies" (p. 73). Thus, not only do costs vary across disciplines, but the relationships between spending and educational output also vary across disciplines. Nonetheless, IPEDS surveys do not collect discipline-based finance data, but three expenditure studies still accounted for the mix of academic disciplines (Blose, Porter, & Kokkelenberg, 2006; Webber & Ehrenberg, 2010; Webber, 2012). Predictably, their findings conflict with expenditure studies that made no adjustments for curricular mix.

Blose, Porter, and Kokkelenberg (2006) also adjusted their model of institutional graduation rates to account for potential variations between institutions in costs by student enrollment level. Conceptually, their enrollment level adjustment reflected the assumption that the cost of educating, say, freshmen and senior engineering students was not the same. Although Pike, Smart, Kuh, and Hayek (2006) examined the relationship between expenditures and engagement rather than retention/graduation, their regression analysis of data from the National Survey of Student Engagement (NSSE) and IPEDS brought this point home. Stratifying their sample by institutional control and student enrollment level, they found, for example, that expenditures for academic support were predictive of active and collaborative learning, student interactions with faculty, and enriching educational experiences first-year students at public institutions, but were not significantly related to the same outcomes for seniors at public institutions or students attending private institutions. At the same time, expenditures for student services were not significantly related to any measures of engagement for students at public institutions but were positively related to interactions with faculty for students at private institutions and positively related to active and collaborative learning just for seniors attending private institutions (Pike et al., 2006).

Institutional control, disciplinary mix, and enrollment distribution are but three sources of institutional heterogeneity that went unobserved in a number of the expenditure studies identified and that research clearly indicates can lead to inappropriate comparisons between institutions and inconsistent findings between studies. Inconsistent findings *within* studies point to the importance of other sources of heterogeneity. Specifically, studies that stratified institution samples by institutional size (Peerenboom, 2012), HBCU status (Pereenbom, 2012), selectivity (Gansemer-Topf & Schuh, 2006; Webber & Ehrenberg, 2010; Webber, 2012), and student financial need (Webber & Ehrenberg, 2010) offer evidence that financial comparisons between institutions depend on these institutional characteristics as well.

For example, Webber and Ehrenberg (2010) showed that student services expenditures had the largest marginal impact on graduation rates at institutions with low median SAT scores and high student financial need, while instructional expenditures had the biggest impact at institutions with high median SAT scores and low rates of student need. In another example, Peerenboom (2012) found a negative relationship between research expenditures and six-year graduation rates for a pooled sample of public institutions. But after stratifying the sample into enrollment quartiles this relationship was significant only for medium-sized institutions (i.e., 5,000 to 9,999 FTE students). In fact, Peerenboom (2012) reported differential impacts of a number of predictors across a number of institutional characteristics. A model of four-year graduation rates for the pooled sample of institutions indicated a negative relationship with research and scholarship expenditures and a positive relationship with SAT scores, enrollment, and residence hall capacity. The same model applied to HBCUs revealed only one significant relationship, between residence hall capacity and graduation rates.

While variations between studies in how researchers handled institution heterogeneity explain a lot of the inconsistencies in the findings from expenditure studies, variations between studies in sample selection, data handling procedures, and model specification also play a role. In some cases, nearly identical models yielded different results. For example, both Peerenboom (2012) and Hamrick et al. (2004) used OLS regression, IPEDS data on close to 450 public four-year institutions, and relatively similar controls to model 6-year graduation rates but arrived at different conclusions about academic support expenditures. But Hamrick and her colleagues (2004) analyzed 1997 graduation rates and 1998 financial data, while Peerenboom (2012) modeled 2009 graduation rates and averaged expenditures over six years to align with the students' enrollment trajectory.

In fact, all but one of the studies that incorporated multiple years of expenditure found no significant association between academic support expenditures and educational outcomes, whereas all of the studies that used a single year of financial data reported a positive relationship. Conceptually, educational expenditures made during a cohorts' sixth year might explain variation between institutions in six-year graduation rates. However, models that account for potential year-to-year variations in expenditure levels over the course of students' progress toward the degree likely offer more precise estimates (for example, as in Webber & Ehrenberg, 2010; Chen, 2012; Peerenboom, 2012; Webber, 2012).

In another example, Webber and Ehrenberg (2010) and Peerenboom (2012) found a negative relationship between funded research expenditures and six-year graduation rates, contrary to prior research (for example, Titus 2006a, 2006b). Pointing out that instructional expenditures actually include departmental research (i.e., research that is not externally funded or separately budgeted), Webber and Ehrenberg (2010) offered this explanation:

> Our intuition is that the institutions with high levels of funded research expenditures per student are also the institutions that have a greater share of their reported instructional expenditures in the form of departmental research. To the extent that we are correct and faculty time spent on departmental research reduces the time available for instruction, this suggests that higher levels of funded research expenditures per student may appear to have a negative effect on graduation rates, when

> instructional expenditures per student are held constant, because of their correlation with unobserved departmental research expenditures. (p. 950)

This speculation suggests that models that do not control for instructional expenditures might predict a positive relationship between funded research expenditures and graduation rates, which is precisely what Kim, Rhoades, and Woodard (2003) found.

Contradictory findings across expenditure studies could also be attributable to the different functional forms of the regression models specified (Webber & Ehrenberg, 2010). Four studies used log transformations of the expenditure variables, arguing that the transformations provided more accurate estimates by accounting for the diminishing marginal productivity of expenditure inputs and improved the interpretability of the results (Ryan, 2004; Pike, Smart, Kuh, & Hayek, 2006; Webber & Ehrenberg, 2010; Chen, 2012). Three other studies estimated the effects of the percentage of total expenditures for each functional category (Titus, 2006a, 2006b; Peerenboom, 2012). Most other studies estimated the effects of per FTE student expenditures by category but at least two studies examined raw expenditures without controlling for institution size/enrollment (i.e., Kim, Rhoades, & Woodard, 2003; Goenner & Snaith, 2004).

Summary of institutional expenditures research. Available research examining the relationship between institutional expenditures and educational outcomes has consistently produced inconsistent findings. This inconsistency is most likely attributable to the fundamental challenges associated with comparing institutions based on institution-level finance data available in IPEDS and the different ways researchers handled institution heterogeneity. Other potential reasons for inconsistent results within and between studies include differences in data handling procedures and model specification. Therefore, given the tenuous nature of institution comparisons based on finance data, comparing the findings from studies designed for this purpose is a tenuous proposition as well.

Still, taken together, these studies have at least three clear implications for future research. First, whenever possible, research should seek to estimate the effects of multiple categories of institutional expenditures on educational outcomes, rather than total expenditures or a single category of expenditures. Second, the estimates should rely on comparisons between institutions with similar missions, demographics, and curricular mixes. Along these line, models that utilize panel data and include institution fixed effects could help advance the research by alleviating the problem of unobserved, time-invariant institution heterogeneity. Third, the most accurate estimates will be based on comparisons not only between similar institutions but also within similar academic disciplines.

Institutional characteristics. Research examining the relationships between institutional inputs such as faculty predictors or expenditures and educational outputs clearly underscores the importance of the structural characteristics of institutions. That is, research accounts for or demonstrates variations in the estimated impacts of these inputs by institutional control (Dolan & Schmidt, 1994; Ehrenberg & Zhang, 2005; Hamrick, Schuh, & Shelley, 2004; Kim, Rhoades, and Woodard, 2003; Bailey, Kienzl, &, 2006; Blose, Porter, & Kokkelenberg, 2006; Gansemer-Topf & Schuh, 2006; Ehrenberg & Webber, 2010; Webber, 2012; Peerenboom, 2012); Carnegie classification

(Ryan, 2004; Goenner & Snaith, 2004; Ehrenberg & Zhang, 2005; Webber & Ehrenberg, 2005; Morrison, 2012); HBCU status (Peerenboom, 2012); and selectivity (Ehrenberg & Zhang, 2005; Webber & Ehrenberg, 2010).

Higher education research specifically drawing on Berger and Milem's (2000) organizational college impact model to examine relationships between institutional characteristics (i.e. structural-demographic features) and student outcomes indicates that institutional size (Titus, 2004), selectivity (Titus, 2004, 2006a, 2006b; Gansemer-Topf & Schuh, 2006; Oseguera & Rhee, 2009), private control (Titus, 2006a; Ryan 2004), and residentiality (Titus, 2004) are positively related to student persistence and/or graduation.

In addition, a growing literature examining how institutions shape underrepresented students' outcomes in STEM has specifically considered selectivity and HBCU status. This literature is discussed next.

Selectivity. In higher education research, institutional selectivity is generally associated with better institutional performance (e.g., graduation rates) (Astin & Oseguera, 2005; Pascarella & Terenzini, 2005). Some research also suggests that selectivity positively contributes to degree completion for underrepresented minorities (for example, Bowen & Bok, 1998). At the same time, studies that account for the self-selection of students into institutions generally find either much smaller "selectivity effects" or no statistical relationship between selectivity and student outcomes (for example, Dale and Krueger, 2002).

With respect to student and institutional outcomes in science and engineering, the role of selectivity is even more ambiguous. Studies indicate that the relationship between selectivity and STEM-related outcomes depends on students' race/ethnicity (Bonous-Hammarth, 2000; Hurtado, Eagan, & Hughes, 2012). Others find that the relationship between selectivity and persistence for URMs depends on whether students attend an HBCU or non-HBCU (Chang, Cerna, Han, & Saenz, 2008). Other evidence suggests that the relationship depends on the outcome of interest (Georges, 1999; Eagan, 2010). Together, this research highlights the nuance in how selectivity may contribute to student outcomes in STEM and why context matters. Evidence from this research also contradicts the controversial and recurring notion that characterizes the performance of underrepresented minority STEM students in terms of their "mismatch" to selective institutions, which is discussed next.

The "mismatch hypothesis" predicts that minority students who attend selective institutions will have worse STEM outcomes than those who attend less selective institutions where their academic credentials are a better match to the institutional average (Alon & Tienda, 2005). For example, a 2010 briefing report of the U.S. Commission on Civil Rights noted:

> Data presented to the Commission showed that success in a STEM major depends both on the student's absolute entering academic credentials and on the student's entering academic credentials relative to other students in the class…There are fewer black and Hispanic physicians, scientists and engineers today than there would have been if colleges and universities had not recruited and admitted black and Hispanic students with significantly lower academic credentials than their average student. (p. 3)

Among the data referenced in the quote above, were findings from two studies that examined racial/ethnic differences in STEM persistence at selective institutions, controlling for students' pre-college academic characteristics (Elliot, Strenta, Adair, Matier, & Scott, 1996; Smyth & McArdle, 2004). Elliot and colleagues (1996) used administrative records from four Ivy League institutions and found that Black students persisted in STEM majors at substantially lower rates (34%) than Hispanic (56%), White (61%) and Asian students (70%). Perhaps more remarkably, they also reported that Hispanic students persisted more and Blacks persisted less than their pre-college academic credentials predicted. Nevertheless, Elliot and others (1996) dismissed the notion that institutional contextual factors might account for the lower than expected African American persistence rates (or higher than expected Hispanic persistence rates) and concluded that the Black students were simply "mismatched" to highly selective institutions as a result of affirmative action policies.

Smyth and McArdle (2004) used multilevel modeling and data on students from 23 selective institutions in the College and Beyond database to examine STEM persistence. They found that disparities in persistence between URMs and Whites as well as men and women were almost completely explained by SAT-math scores, which they offered as evidence of the validity of the mismatch hypothesis. Their model also resulted in no statistical association between selectivity and STEM persistence, controlling for student demographic and academic characteristics – though this could have resulted from using a relatively homogenous sample of institutions with limited variation between institutions.

Other scholars have argued that the "mismatch" hypothesis is fundamentally flawed (for example, Alon & Tienda, 2005; Tapia, 2009; Hurtado, Newman, Tran, & Chang, 2010). These studies suggest that high-status institutions may foster STEM environments marked by competition, weed-out mentality, faculty focused more on research than teaching, and limited role models for URMs. These are precisely the conditions that qualitative research (discussed earlier) suggests decrease STEM persistence for URMs. Moreover, the limited range of institutions used in studies supporting the notion of mismatch offer little insight about how selectivity plays out for URMs over a broader institutional spectrum.

Seemingly consistent with the mismatch hypothesis, Bonous-Hammarth (2000) found a negative relationship between selectivity and four-year persistence in STEM for URMs, using data from the Cooperative Institutional Research Program's (CIRP) 1985/1989 freshmen and follow-up surveys and controlling for pre-college academic achievement. Bonous-Hammarth (2000) speculated that the negative relationship was attributable to institutional climate factors such as stereotype threat but was unable to test this hypothesis due to data limitations. Chang, Cerna, Han, and Saenz (2008) analyzed data on the 2004 CIRP freshman cohort and found that first-year persistence in biomedical and behavioral sciences was negatively related to institutional selectivity for all students, controlling for student and institutional characteristics. Unpacking this, a separate analysis revealed that among HBCUs, URM persistence increased with institutional selectivity; but among non-HBCUs persistence decreased with selectivity (Chang et al., 2008). Also analyzing data on the 2004 CIRP freshman cohort, Newman

(2011a) found no statistical relationship between selectivity and five-year engineering or computer science degree completion versus non-STEM completion for African Americans. Hurtado, Eagan, and Hughes (2012) defined STEM more broadly and offered support for both sides of the selectivity debate. Their analysis of 2004 CIRP freshmen suggested that selectivity was positively related to degree completion (versus dropout) but not statistically related to retention in STEM for all students. For Black students, selectivity was negatively related to four- and five-year STEM degree completion but not statistically related to six-year STEM degree completion (Hurtado, Eagan, & Hughes, 2012).

A few studies have used institutions as the unit of analysis to examine the relationship between selectivity and URM outcomes in STEM. For example, Roper's (2011) descriptive analysis of STEM degree production at over 1500 institutions using the Education Trust's *College Results Online* database indicated that institutions in the lowest selectivity quintile were most likely to have very high STEM degree production rates. However, Roper's (2011) inclusion of institutions in U.S. territories like Puerto Rico makes it difficult to compare her results to most other analyses, which do not include these institutions. Georges (1999) found a positive relationship between selectivity and retention rates in engineering, for minorities and non-minorities. Georges' (1999) findings may be questionable since the retention rates were not directly measured but computed based on aggregate enrollment and completions data reported to the Engineering Workforce Commission.

Summary of selectivity studies. Studies that have considered how selectivity might contribute to students' persistence processes and outcomes in STEM have produced mixed findings. However, this review suggests that while selectivity contributes to degree attainment relative to dropout, it is not necessarily related to retention in STEM per se. Different studies drawing on the same data indicate that the relationship between selectivity and STEM persistence varies based on student race/ethnicity, how researchers operationalized STEM, the STEM outcome examined, and HBCU status. Therefore, future studies examining the relationship between selectivity and educational outcomes should account for these potential sources of variation.

Historically Black colleges and universities. Descriptive reports commend HBCUs for a longstanding record of producing African American STEM baccalaureates, suggesting, "In almost every STEM field, HBCUs lead the nation's larger, better-equipped colleges in producing Black graduates" (Southern Education Foundation, 2005, p. 5). While generalizations like this are debatable and some of the oft-quoted statistics about the role of HBCUs in STEM are certainly outdated, HBCUs remain key players. Recent data suggest that HBCUs, which represented 3% of all four-year postsecondary institutions and enrolled roughly 16% of African American students in four-year institutions in 2010, conferred 20% of natural science and engineering bachelor's degrees awarded to African Americans in 2010 (Ransom, in preparation).

That HBCUs produce a disproportionate share of STEM graduates is seen as remarkable for at least four reasons. First, HBCUs represent a small segment of STEM degree-granting institutions, for example, although HBCUs produced 20% of Black engineering baccalaureates in 2010, HBCUs represent only 16 of the 399 (4%) institutions with ABET-accredited engineering programs HBCUs (Ransom, in preparation; ABET, 2012). Second, HBCU students have, on average, lower socioeconomic status backgrounds and lower high school GPAs and college entrance exam scores than their non-HBCUs peers (Allen, 1992; Kim, 2002; Kim & Conrad, 2006; Li & Carroll, 2007), both of which have been linked to lower rates of STEM persistence and degree attainment (Elliot et al., 1996; Smyth & McArdle, 2004). HBCUs also have lower institutional resources (i.e., proportions of faculty with doctorates, average faculty salaries, per student instructional expenditures, and endowments) and lower STEM resources (e.g., research and development funding and infrastructure) than non-HBCUs (Gasman et al., 2010; Kim, 2002; Kim & Conrad, 2006; Suitts, 2003; Swail, Redd, & Perna, 2003; Bennof, 2009; Matthews, 2011; Clewell, de Cohen, & Tsui, 2010).

Despite some evidence of a disproportionate contribution by HBCUs in educating African Americans in science and engineering fields, little available research examines relationships between HBCU attendance or HBCU status and STEM educational outcomes. Without a doubt, this is largely a consequence of the newness of research examining institutional predictors of STEM outcomes. Nevertheless, the few studies that attempt to make this connection do so by either estimating an HBCU "effect" quantitatively or by examining (mostly qualitatively) the HBCU environment.

Estimating HBCU "effects." Some quantitative research attempts to estimate HBCU effects by including HBCU attendance (student-level) or HBCU status (institution-level) as a predictor or stratification variable in models examining student or institution-level educational outcomes. Analyses of cohorts that attended college in the 1970s and 80s generally indicated that HBCU status was positively related to degree completion, irrespective of discipline and controlling for students' pre-college academic characteristics (Cross & Astin, 1981; Ehrenberg & Rothstein, 1994; Kane, 1994; Pascarella, Smart, Ethington, & Nettles, 1987). Yet reflecting what Pascarella and Terenzini (2005) called an "empirically muted discussion," current studies are sparse and more equivocal. And depending on data and methodology, studies suggest no statistical relationship between HBCU attendance and degree completion (Kim & Conrad, 2006), a positive relationship (Ryan, 2004), or differential relationships by gender (Sibulkin & Butler, 2005).

With respect to student outcomes in science and engineering, older studies suggest that African American students at HBCUs are more likely to choose STEM majors than those at non-HBCU (Thomas, 1987, 1991; Trent, 1991; Trent & Hill, 1994; Wenglinsky, 1997). However, only a handful of recent studies, most of which were conducted by researchers affiliated with the UCLA Higher Education Research Institute (HERI), directly examine the relationship between HBCU attendance/status and STEM outcomes (Chang et al., 2008; Newman, 2011; Eagan, 2010; Hurtado, Eagan, & Hughes, 2012).

With funding from the National Institutes of Health and the National Science Foundation, HERI researchers have published a number of studies that advance understanding about the factors contributing to underrepresented minority students' success in STEM fields, with particular attention to the role institutional contexts and characteristics. Chang and colleagues (2008) used logistic regression to examine first-year persistence of biomedical and behavioral science majors. Based on a sample of close to 3000 students at 159 institutions, they found that as a predictor, HBCU status was not statistically related to URM persistence. However, selectivity "effects" depended on HBCU status applied as a sample stratification variable, as discussed in the previous section.

Hurtado and colleagues' (2008) used multilevel modeling to estimate the probability of first-year students' participation in health science research and detected no statistical association with HBCU attendance. In another multilevel study, Hurtado, Eagan, and Hughes (2012) examined how institutional contexts contributed to STEM degree completion for URMs. In a pooled model of URMs, HBCU status was not a significant predictor of four-, five-, or six-year STEM completion; however, disaggregating the sample revealed that Black students at HBCUs were 11.3 percentage points more likely complete a STEM degree in four years relative to Blacks at non-HBCUs, controlling for student and institution-level characteristics. HBCU status was not statistically related to five- or six-year completion, however (Hurtado, Eagan, & Hughes, 2012).

Another HERI study by Christopher Newman (2011a) suggested no statistical association between HBCU status and five-year engineering and computer science bachelor's degree completion for African Americans. However, Newman (2011a) found that HBCU engineering and computer science students were less likely to switch to non-STEM majors. Finally, Eagan (2010) examined two different STEM outcomes for

URMs – STEM degree production efficiency using institutions at the unit of analysis and seniors' aspirations for various advanced degrees in a multilevel framework. While HBCU status was statistically unrelated to degree production efficiency, controlling for other institutional characteristics, STEM seniors attending HBCUs had a 21.5% higher average probability of aspiring to earn a Ph.D. and a 30% higher average probability of aspiring to earn an M.D. relative to URM seniors at non-HBCUs (Eagan, 2010).

Outside of the HERI studies, few researchers have examined relationships between HBCU attendance/status and outcomes in STEM. Georges (1999) descriptive analysis considered the extent to which institutions' retention rate of URMs in engineering differed by various institutional characteristics. Her descriptive analyses indicated that, on average, the retention rates of Blacks in engineering were higher at HBCUs (36.1%) than the national average for Black students (32.3%) (Georges, 1999). However, a subsequent regression model estimating engineering retention rates did not include HBCU status as a predictor (Georges, 1999).

Despite the dearth of quantitative research estimating the effects of HBCU attendance/status on student outcomes in STEM overall, a substantial literature considers the role of HBCUs as the baccalaureate origin institution for African American STEM doctorate degree recipients (Pearson & Pearson, 1985; Solórzano, 1995; Leggon & Pearson, 1997; Wolf-Wendel, 1998; Wolf-Wendel, Baker, & Morphew, 2000; Burelli & Rapoport, 2008; Hubbard & Stage, 2010; Sibulkin & Butler, 2011). This research – in which baccalaureate origin institutions are the unit of analysis – consistently indicates that, in absolute terms, HBCUs are the baccalaureate origins of a disproportionate share of Black STEM doctorate recipients. At the same time, these studies demonstrate that understanding the contribution of baccalaureate origin institutions to the production of doctorate degree earners is not as simple as rank ordering institutions by the number of alumni who become doctorate recipients. That is to say, institutions that produce relatively large numbers of African American baccalaureates (i.e., HBCUs) naturally have larger pools of potential doctorate recipients. Therefore, researchers have come up with a number of productivity indices or ratios designed to account for the size of an institution's pool of potential doctorate recipients (See Sibulkin & Butler, 2011 for a review). And some studies suggest that after adjusting for the number of bachelor's degrees awarded to African Americans, the number of doctorate recipients from HBCUs is actually unremarkable or on par with non-HBCUs (Burelli & Rappaport, 2008; Sibulkin & Butler, 2011). Other studies disagree (e.g., Wolf-Wendel, 1998; Wolf-Wendel, Baker, & Morphew, 2000). The use of different formulae gives rise to different results, interpretations, and implications. In one noteworthy exception, however, Hubbard and Stage's (2010) baccalaureate origin study ranked comprehensive public institutions' production of URM STEM doctorates without computing a productivity ratio. Instead they analyzed baccalaureate origins by comparing each institution's actual performance to its predicted performance, which they computed using coefficient estimates from a model regressing the number of doctorates on measures of enrollment and institutional quality (Hubbard & Stage, 2010). They found that six of the top ten "unexpected" producers of URM STEM doctorates were HBCUs.

Examining HBCU environments. Researchers have also examined the ways that HBCU environments might foster success in STEM for Black students. This research focuses on exemplary HBCUs that have demonstrated success in STEM (e.g., Brazziel & Brazziel, 1997; Culotta, 1992; Southern Education Foundation, 2005; Perna et al., 2009) and comparisons between Black students' experiences in STEM at HBCUs versus non-HBCUs (e.g., Wenglinsky, 1997; Suitts, 2003; Fries-Brit, Younger, & Hall; 2010; Lent et al., 2005; Brown, Morning, & Watkins, 2005). By and large, this literature indicates that HBCUs provide supportive and affirming STEM environments, with cooperative rather than competitive peer climates (Hurtado et al., 2009; Perna et al., 2009; Fries-Britt, Younger, & Hall, 2010). Likewise, this research suggests that HBCU STEM students tend to have more positive perceptions of their educational climates and experiences (Brown, Morning, & Watkins, 2005) as well as higher self-efficacy and post-baccalaureate educational aspirations relative to African American STEM students at non-HBCUs (Lent et al., 2005).

Summary of HBCU studies. Qualitative and descriptive research consistently finds that HBCUs produce disproportionate shares of African American STEM graduates and eventual doctorate recipients, provide supportive and affirming environments, and foster self-efficacy, among a number of positive outcomes. But, there is not yet a compelling body of quantitative evidence corroborating these findings on a broader, generalizable scale. Still, some research by UCLA's Higher Education Research Institute has begun addressing this void in the knowledge. The HERI studies have found that the relationship between selectivity and STEM persistence depends on HBCU status (Chang et al., 2008); engineering and computer science majors at HBCUs were less likely to switch to a non-STEM major (Newman, 2011); HBCU attendance was associated with higher 4-year STEM degree completion rates among Black students (Hurtado, Eagan, & Hughes, 2012); and HBCU attendance was positively related to graduate and professional degree aspirations among URMs (Eagan, 2010), for example.

Aggregate student characteristics. As discussed at the beginning of this chapter, STEM higher education research has traditionally focused on student-level predictors of student-level outcomes, finding that pre-college academic preparation is the main predictor of STEM persistence and degree completion (e.g., Elliot et al., 1996; Smyth & McArdle, 2004), with minority underrepresentation in STEM also attributed to lower levels of self-efficacy, cultural congruity, ambition, or commitment to STEM (e.g., Leslie, McClure, & Oaxaca, 1998; Seymour & Hewitt, 1997). Along these lines, some research examining institutional predictors of URM outcomes in STEM considers the contribution of aggregate student characteristics, such as academic preparation. In particular, Eagan (2010) found that the average SAT scores of the entering class was positively related and the proportion of URM undergraduates was negatively related to STEM bachelor's degree production efficiency for URM students. Ostreko (2012) found a positive relationship between the proportion of URM engineering undergraduates and master's degree production for URMs as well as a positive relationship between the proportion of URM engineering master's students and doctorate degree production for URMs.

Like STEM-specific research, broader higher education research has also tested relationships between aggregate student characteristics and degree completion. For example, Titus (2006a) found that the average socioeconomic status and racial/ethnic diversity of the student body were positively associated with degree completion, irrespective of major field. Webber & Ehrenberg (2010) and Webber (2012) showed that the estimated impact of institutional expenditures on graduation rates depended on aggregate student financial need as measured by Pell Grant dollars.

Summary of Current Research

The research surveyed in this chapter was selected to illustrate the ways that scholars have [at least implicitly] conceptualized institutional inputs, institutional characteristics, and aggregate student characteristics in examining educational outcomes in STEM specifically, and, to a lesser extent, in higher education broadly. This research is primarily framed by interactionalist, organizational or economic (i.e., production function) theoretical perspectives.

Institutional inputs that have been linked to higher education/STEM outcomes include programmatic interventions, faculty predictors, and institutional expenditures. Available research is largely suggestive of positive effects of summer bridge, undergraduate research, and comprehensive retention and support programs on a range of student outcomes in STEM but provides little conclusive evidence due data and methodological limitations. In general, faculty predictors have been neglected as potential predictors of student- or institution-level outcomes. But, by and large, this research associates non-tenured/tenure-track instructors with worse outcomes; finds differential effects across institutional control, Carnegie classification, academic disciplines, and student race/ethnicity; and hints that faculty-student ratios, faculty race/ethnicity, and faculty gender may predict various success outcomes for URM STEM students. Research examining the relationship between institutional expenditures and educational outcomes has consistently produced inconsistent findings, most likely due to the challenges associated with comparing institutional finance data and the different approaches to handling institution heterogeneity.

That institutional characteristics contribute to student outcomes in higher education is clear from research on the relationships between institutional inputs and educational outcomes, since the estimated effects of institutional inputs differ by institutional control, Carnegie classification, selectivity, and HBCU status, for example (e.g., Scott, Bailey, and Kienzl, 2006; Webber & Ehrenberg, 2010; Peerenboom, 2012) . The role of institutional selectivity and HBCU status has also been directly explored in the STEM higher education research (Chang et al., 2008). Findings suggest that selectivity contributes to degree completion relative to dropout but that the relationship between selectivity and STEM persistence varies based on student race/ethnicity, STEM discipline, the specific outcome examined, and HBCU status. Qualitative and descriptive research consistently finds that HBCUs provide supportive and affirming environments and produce disproportionate shares of African American STEM graduates and eventual doctorate recipients but empirical evidence of statistically significant relationships between HBCU attendance/status and STEM persistence/completion is limited.

Lastly, drawing on the findings from traditional STEM higher education research, scholars investigating how institutional factors shape student outcomes in STEM often control for student academic preparation either at the student-level (in multilevel studies) or in the aggregate (in institution-level analyses), since academic preparation is positively related to STEM success. Findings about the impact student racial/ethnic composition on URM STEM outcomes have been mixed (Eagan, 2010; Ostreko, 2012). And the impact of expenditures on institutional graduation rates varies by aggregate student financial need (Webber & Ehrenberg, 2010).

Limitations of Current Research

The literature reviewed, particularly multi-institutional STEM-focused studies, is limited in terms of scope, data, and methodologies. With respect to scope, STEM is consistently operationalized as arbitrary assortments of natural, social, behavioral science and/or engineering majors, which gives rise to a lack of consistency across studies in defining STEM major fields, confounds the insights gleaned, inhibits meta-analyses of the work, and obscures fundamental differences between STEM fields (and their students). Potential heterogeneity in students' experiences and outcomes in STEM is also diminished by the tendency to pool underrepresented minorities. For example, descriptive evidence from some HERI studies suggest variations within the URM category in students' STEM outcomes; descriptive evidence presented in Chapter 1 suggests variations in national outcomes within STEM and variations within the URM category in students outcomes in engineering.

These limitations notwithstanding, the absence of more narrowly defined quantitative studies examining relationships between institutional predictors and underrepresented minorities' STEM educational outcomes is likely attributable to the dearth of robust, multi-institution data sets involving URM STEM students. For instance, national surveys such as the CIRP surveys target undergraduate populations broadly, resulting in too few cases for reliable analyses within specific STEM fields and/or specific racial/ethnic subpopulations.

Three additional data limitations are apparent from studies examining the role of institutional inputs on educational outcomes. First, these studies rely almost exclusively on institution-level data provided in IPEDS. However, IPEDS does not include STEM- or program-level faculty or expenditures data, which limits analyses to broad institutional inputs that could lead to aggregation bias. That is, institution-level faculty and expenditures data might not offer valid measures for understanding STEM-specific phenomena. Second, the research reviewed draws primarily on cross-sectional data that can only provide a snapshot view of the relationships of interest, limiting the generalizability and interpretation of findings. Third, the comparability and integrity of financial data across institutional samples is not explicitly addressed in studies examining the relationships between expenditures and institutional graduation rates.

Methodological limitations of the multi-institution studies reviewed are at least four-fold. First, few studies explicitly address the problem of missing data. Neither the extent of missingness nor methods for handling missing data are typically presented. Second, owing to the cross-sectional structure of the data analyzed, the potential for omitted variables bias is inescapable in the studies reviewed. The expenditures studies clearly demonstrated the limits of analyses that fail to adequately account for between institution heterogeneity, either by including control variables or by stratifying the sample. Third, although some of the studies reviewed include multiple years of data in pooled OLS regression models, no studies employ panel data methods to exploit the structure of longitudinal data and (partially) mitigate the problem of omitted variables bias. Likewise few STEM-related studies offer longitudinal perspectives on URM outcomes in STEM. Fourth, few STEM-focused studies examine institution-level outcomes, which would inform institutional practice and address accountability concerns. Fifth, the higher education production function studies almost always fail to test the fundamental assumption that institutions maximize their outputs.

Need for Additional Research

In order to expand the knowledge on the role of institutions in determining underrepresented minority students' outcomes in STEM, more systematic analysis that builds on the broad approaches already established is necessary. Specifically, the extent to which broad findings about URMs in STEM higher education are generalizable to specific racial/ethnic groups in specific STEM disciplines such as engineering should be explored. Also, given the inconsistencies in the estimated effects of institutional inputs on educational outcomes, research is required that relies on comparisons between or within institutions with similar missions, structures, and curricular mixes. For example, stratification of institutions by control, Carnegie classification, etc., should diminish between-institution unobserved heterogeneity that could potentially confound findings. More research is needed drawing on and exploiting panel data to also limit the potential for unobserved heterogeneity bias. Finally, with respect to higher education production function studies, more research is needed to investigate whether institutions produce different levels of educational output with the same set of inputs, for example, through efficiency analyses.

CHAPTER 3 – RESEARCH DESIGN

In this chapter, I describe my approach to advancing the knowledge about how institutional factors contribute to STEM educational outcomes. First, I outline the research questions that guide the study. Then, I provide an overview of the data, sample, and variables used in the study. After outlining the variables selected, I describe the methods used to conduct the analyses. Finally, I end the chapter by discussing the limitations of the study design.

Research Questions

In this quantitative study, I use institution-level, longitudinal data and a production framework to explore how U.S. engineering schools' labor inputs contribute to engineering bachelor's degree production for underrepresented minorities in general and for African Americans specifically. In addition, I stratify the data to explore the potential for differential impacts of faculty inputs by institutional contexts. The study is designed to address the following research questions:

1. How did engineering colleges and schools' bachelor's degree output by race/ethnicity and labor (faculty) inputs vary during the sample period, 2005 to 2011? Were these trends consistent across institutional contexts?
2. Do engineering colleges/schools' labor inputs similarly predict bachelor's degree output for all students, underrepresented minorities, and African Americans, controlling for characteristics of the college/school and broader institutional characteristics?

a. Do selected measures of physical and financial capital predict engineering degree output by race/ethnicity?

b. Do selected institutional expenditure measures predict engineering degree output by race/ethnicity?

c. To what extent do estimates differ when controlling for past degree output?

3. To what extent are engineering schools/colleges maximizing bachelor's degree production for all students, underrepresented, and African Americans based on the models specified in RQ2?

Data

This study used data drawn from five sources: the American Society for Engineering Education's (ASEE) annual Survey of Engineering and Engineering Technology Colleges, the National Science Foundation's Survey of Research and Development Expenditures at Universities and Colleges, the U.S. Department of Education National Center for Education Statistics' Integrated Postsecondary Education Database (IPEDS), the IPEDS Delta Cost Project Database, and Barron's Profiles of American Colleges. All data sources were linked using institutional ID numbers, names, and addresses.

The ASEE is a nonprofit organization founded in 1893 whose mission is to promote engineering education through a range of endeavors in the interest of a membership of more than 12,000 individuals and organizations (ASEE, 2012). ASEE administers the Survey of Engineering and Engineering Technology Colleges to U.S. and Canadian engineering schools and colleges that have at least one ABET-accredited engineering program. The data collected are published in ASEE's online directory of programs, the *Annual Profiles of Engineering and Engineering Technology Colleges* book and a restricted-access electronic database (ASEE, 2012). The online database contains annual records for over 370 engineering schools/colleges from 1998 to 2011 including such information as: undergraduate and graduate enrollment by level and intensity; number of bachelor's, master's, and doctoral degrees conferred; number of tenured/tenure-track faculty; numbers of "other teaching" and research personnel; and externally funded research expenditures by source (e.g., industry, government, non-profit organizations, etc.). All data are reported by engineering discipline/department; faculty and student data have also been reported by race/ethnicity and gender since 2005. The ASEE data served as the primary source for engineering degree outputs and faculty inputs analyzed in this study.

The Survey of Research and Development Expenditures at Universities and Colleges, which was renamed the Higher Education Research and Development (HERD) Survey in 2010, has been administered annually by the NSF annually since 1972 (NCSES, 2013). The survey collects information on R&D expenditures by academic discipline as well as by source of funds from research-performing, non-profit postsecondary institutions. Prior to 2010, the target population for the HERD survey included only institutions with R&D spending and degree programs in science and engineering, but as of the 2010 survey the target population was expanded to include all institutions with $150,000 or more in R&D spending in any field (NCSES, 2013). In 2011, the most recent survey year, data were collected from 912 institutions. R&D data on all participating institutions for survey years 1972 to 2011 are available through the National Center for Science and Engineering Statistics' Integrated Science and Engineering Resources Data System, WebCASPAR. The HERD survey provided additional data on engineering schools' labor and capital inputs analyzed in this study.

Every U.S. postsecondary institution that participates in federal student financial aid programs is required to participate in IPEDS surveys, reporting data on institutional characteristics, enrollments, program completions, graduation rates, faculty and staff, finances, institutional prices, and student financial aid (NCES, 2013). This study drew data on broad institutional characteristics from IPEDS available through the online IPEDS Data Center.

The IPEDS Delta Cost Project Database includes longitudinal data derived primarily from IPEDS finance data for 1987 to 2010, which have been "harmonized in order to mitigate changes in financial reporting standards over time by employing industry-accepted manipulations of the data" (Lenihan, 2012, p. 2). The Delta Cost Project Database also includes imputations of missing data where possible and data organization to ease longitudinal analyses. Delta Cost data provided information about broader institutional inputs analyzed in this study.

Finally, Barron's College Admissions Competitiveness Index was used to operationalize institutional selectivity. This index uses multiple factors to rate institutions on a selectivity continuum from "noncompetitive" to "most competitive." These factors are based on the entering freshman cohort and include: students' entrance exam scores; students' academic ranking in high school; institutions' class rank and GPA admissions requirements; and the percentage of applicants accepted by institution (Barron's Educational Series, 2013).

Sample

Since 1932, ABET (formerly, the Accreditation Board for Engineering and Technology) has been the primary accrediting agency for technical higher education programs in the U.S. and abroad – including engineering, engineering technology, computing, and applied science programs (ABET, 2013). As of October 2012, 399 U.S. colleges and universities had at least one ABET-accredited engineering degree program; these institutions make up the target population of this study. Because the key measures included in the analysis (and discussed in the next section) were not collected by ASEE until 2005, the sample period includes 2005 up to the most recent survey year, 2011. Over the sample period, ASEE data include records for 351 U.S. engineering schools/colleges with an ABET-accredited degree program in at least one of the 19 disciplines listed in Table 3.1. These institutions constitute 88% of the target population. Eliminating for-profit institutions, institutions located in Puerto Rico, institutions that did not report student enrollment and completions by race/ethnicity, institutions that did not report faculty information and institutions for which complete records were not available over the entire sample period, yielded 324 unique institutions (represented by N) over 7 years or 2,268 institution-year observations (represented by n).

Table 3.1 ASEE engineering disciplines.

Aerospace	Mechanical
Architectural	Metallurgical & Materials
Biological & Agricultural	Mining
Biomedical	Nuclear
Chemical	Other
Civil	Petroleum
Civil/Environmental	Engineering Management
Electrical/Computer	Eng. Science & Eng. Physics
Engineering (General)	Environmental
Industrial/Manufacturing	

Source: ASEE, 2012.

Additional sample restrictions were necessary to reflect the study's focus on bachelor's degree production for underrepresented minorities in engineering. First, analyzing data compiled in NSF's WebCASPAR system revealed that 453 institutions conferred at least one bachelor's degree to underrepresented minorities and 409 conferred at least one degree to African Americans over the sample period, 2005 to 2011. Of the programs conferring degrees to URMs, 365 were ABET-accredited, of which 336 (92%) participated in the ASEE survey. Likewise, 351 of the programs conferring degrees to African Americans were ABET-accredited, of which 326 (92%) participated in the ASEE survey. However, several of these institutions conferred relatively few degrees to URMs during the sample period. For example, 40 programs awarded a total of five or fewer engineering bachelor's degrees to URMs over the seven-year period; 74 programs awarded five or fewer engineering bachelor's degrees to African Americans.

Therefore, institutions with relatively few URM undergraduates/baccalaureates were excluded from the analyses. Specifically, the complete sample of 324 ASEE institutions was stratified into two sets of quartiles, according to the total number of bachelor's degrees conferred to URM and Black engineering students over the sample period. Most analyses drew on the top three quartiles of ASEE participant institutions conferring bachelor's degrees to URMs (N = 250 institutions, n = 1750). A few alternative/sensitivity analyses focused specifically on Black students and drew on the top two quartiles of institutions conferring bachelor's degrees to African Americans (N = 167, n = 1169). Tables 3.2 and 3.3 summarize the samples used in the analysis. Table A.1 in the appendix lists the 324 institutions that comprised the complete sample.

Table 3.2 Summary of complete sample, ASEE participant institutions, 2005-2011.

Sample	n	N	Percentage of ABET-Accredited Institutions
Initial	2417	351	88.0
Restricted*	2268	324	81.2

N = number of institutions
n = number of institution-year observations
*Excludes for-profit institutions, institutions located in Puerto Rico, institutions not reporting enrollment/completions by race/ethnicity, institutions not reporting faculty information, and institutions not participating in all survey years (2005-2011).

Table 3.3 Quartile cut-points for total number of engineering bachelor's degrees conferred to underrepresented minorities and African Americans during 2005to 2011 and number of institutions (and observations) in each quartile.

	Total number of degrees, 2005-2011	
Percentile	To URMs	To African Americans
25th	29.3	8.3
50th	93.0	35.0
75th	254.8	93.8
Quartiles	N (n)	N (n)
1	74 (518)	73 (511)
2	82 (574)	84 (588)
3	84 (588)	83 (581)
4	84 (588)	84 (588)
Total	324 (2268)	324 (2268)

N = number of institutions
n = number of institution-year observations

Variables

The selection of variables used to model engineering bachelor's degree production was guided by microeconomic producer theory and prior specifications of the higher education production function. Given my focus on Black and other underrepresented minority students, variable selection was also informed by research on URM outcomes in science and engineering, which was laid out in Chapter 2. Of course, variable selection was also constrained by the measures available in the data used.

Dependent (output) variables. Although higher education produces a range of outputs – Hopkins (1990) catalogued 49 potential measures – this study focuses on the instructional or education outputs of colleges and universities. Salerno (2003) notes that "in nearly all empirical studies of higher education production and costs: education output is almost exclusively proxied by physical headcounts of full time equivalent (FTE) enrollments or number of degrees" (p. 25). While such purely quantitative measures are not ideal given the importance of intangible, qualitative features of higher education products like the quality of the education students obtain or the quality of effort put forth by students, most scholars readily acknowledge the lack of appropriate, informative measures of these features (Hopkins, 1990; Lewis & Dundar, 2001, Salerno, 2003).

Kelly (2009) argues that among the three most common measures used to compare performance across higher education institutions or states, absolute numbers of degrees is the most basic and most problematic. Numbers of degrees can shed light on the volume of production but is not a fair measure for comparing institutions particularly of different sizes. Graduation rate – the percentage of first-time, full-time, degree-seeking students who graduate within 150% of program time – is the most common completion metric. However, this measurement of graduation rates does not account for part-time students or students who transfer into or out of an institution, who together make up an increasing share of college-goers. Kelly (2009) contends that compared to graduation rates, the number of degree completions per full-time equivalent (FTE) students enrolled provides a better appraisal of an institution or system's ability to produce degrees. Institutions that produce fewer degrees relative to their enrollment are clearly less productive. And, unlike graduation rate, the FTE denominator encompasses the entire student body of the institution.

In this study, the dependent variable used to represent the undergraduate educational output of engineering schools and colleges is defined as follows:

1. The number of engineering bachelor's degrees conferred per FTE undergraduate enrollment in engineering;
2. The number of engineering bachelor's degrees conferred to URMs per FTE URM undergraduate enrollment in engineering; and
3. The number of engineering bachelor's degrees conferred to African Americans per FTE African American undergraduate enrollment in engineering.

Rather than simply examining the absolute numbers of underrepresented minorities earning degrees at various institutions, which invariably favors institutions with large URM enrollments, these measures are concerned with institutional productivity – what are institutions able to do with the URM students they have? Thus, these measures combine the precedents of higher education production function studies and policy and practice related to higher education performance.

Independent variables. Producer theory states that maximum firm output is a function of capital and labor inputs. Yet most higher education economists recognize that production in higher education is more complex than in other sectors of the economy (Paulsen & Toutkoushian, 2006). Similar to outputs, specification of inputs is typically limited to quantitative measures, and due to the "black box" nature of the higher education production function, there is no firm conceptual consensus to guide its specification (Lewis & Dundar, 2001; Salerno, 2003). Therefore, drawing on organizational frameworks used to examine how institutions contribute to educational outcomes (in particular, Berger and Milem [2000]) and prior specifications of the higher education production function (e.g., Webber and Ehrenberg [2010]), this study expands the notion of inputs to include aspects of the institutional context.

The independent variables used in this study can be classified as institutional inputs, institutional characteristics, and student characteristics. For the most part, "institution" refers to engineering schools and colleges. However, given the limitations of the available data, inputs and characteristics of the broader institution served as proxies for the engineering schools/colleges in some cases.

Institutional inputs (explanatory variables). As discussed in Chapter 2, academic labor (faculty/staff and students) is viewed as the most important input driving higher education production and a practical lever for policymakers and institutional decision-makers. Specifically, higher education production functions almost universally include proxies for faculty labor inputs, such as instructional expenditures (which are mainly comprised of faculty salaries) and faculty characteristics (e.g., Salerno, 2002, 2003; Webber & Ehrenberg, 2010). As well, empirical evidence presented in Chapter 2 suggests that the racial/ethnic and gender composition of faculty may influence STEM outcomes for underrepresented minorities.

In this study, engineering faculty inputs are the explanatory variables of interest. I operationalize faculty inputs through six separate measures:

1. Proportion of FTE non-tenured/tenure-track teaching faculty in engineering;
2. Proportion of FTE research faculty in engineering (of the entire FTE engineering faculty);
3. FTE Faculty to FTE undergraduate student ratio in engineering;

4. Proportion of underrepresented minority tenured/tenure-track engineering faculty;

5. Proportion of female tenured/tenure-track engineering faculty; and

6. Funded expenditures for engineering research per FTE engineering undergraduate.

In each case, part-time engineering faculty counts were reported in FTEs, which were simply added to full-time headcounts in order to generate necessary FTE faculty figures. However, part-time student enrollments had to be converted to FTE headcounts then added to the full-time headcounts to produce FTE undergraduate enrollment figures. I multiplied part-time enrollments by factors drawn from the U.S. Department of Education's annual Digest of Education Statistics to estimate the FTE student headcounts. For four-year public and private institutions, the conversion factors were .403543 FTE/part-timer and .392857 FTE/part-timer, respectively (U.S. Department of Education, 2013).

Physical and financial capital inputs are rare in empirical studies of higher education production (Salerno, 2002). Capital, such as buildings, land, and financial assets, are difficult to reconcile across institutions due to differences in accounting practices. Economic concepts are useful for understanding other reasons for excluding capital from empirical studies of higher education production. Economists assume that production inputs can be either fixed or variable; fixed inputs do not change and variable inputs do change with the changes in the rate of output. Economists also distinguish between the short run and long run, where the short run is a period in which there is at least one fixed input while all inputs are variable over the long run (Brinkman, 2007).

Higher education capital (e.g., buildings, land, endowment assess) is more often fixed over the typical short run periods examined in production function studies. Thus, higher education capital is not a realistic policy lever, as changes in capital are not likely to have short run impacts on education output.

Nevertheless, this study explores alternative specifications of the engineering degree production function that tests these notions about the influence of capital inputs. Specifically, the analysis includes the following measures:

1. Funded expenditures for engineering research equipment per FTE engineering undergraduate enrollment; and
2. (Institution-level) Revenue from affiliated entities, private gifts, grants and contracts, investment returns and endowment earnings per FTE undergraduate enrollment. (I initially intended to include endowment revenue per FTE; however, institutions stopped reporting endowment earnings separately to IPEDS in 1997 [FASB reporting institutions] and 2002 [GASB reporting institutions]).

Most recent higher education production function studies operationalize institutional inputs in terms of institutional expenditures by category (e.g., Blose, Porter, & Kokkelenberg, Webber & Ehrenberg, 2010; Webber, 2012). Institutional expenditures are used to represent both faculty labor (e.g., instruction and/or research) and staff or physical resources (e.g., computing, libraries, support services). Nonetheless, program-specific expenditure data are generally not available. Kelly (2009) contends that the lack of available data on the costs of producing degrees is the “most difficult barrier to conducting sound productivity analyses in postsecondary education” (p. 6).

Notwithstanding this limitation, alternative specifications of the models estimated in this study include broader institutional expenditures by category:

1. Instructional expenditures per FTE undergraduate enrollment;
2. Academic support expenditures per FTE undergraduate enrollment;
3. Student support services expenditures per FTE undergraduate enrollment;
4. Funded research expenditures per FTE undergraduate enrollment; and
5. Total education and general expenditures per FTE undergraduate enrollment.

Each of these expenditure categories was defined in Chapter 2 and refers to institution- rather than engineering-level spending. All institutional financial data were adjusted for inflation using the implicit price deflator for GDP (i.e., GDP deflator), which is available through the Bureau of Economic Analysis of the U.S. Department of Commerce (U.S. Department of Commerce, 2013).

Aggregate student characteristics (control variables). Berger and Milem's (2000) organizational college impact model emphasizes the importance of student characteristics and peer context for student outcomes, and other research reviewed in Chapter 2 specifically touches on URM outcomes in STEM. In addition, Salerno (2002) demonstrated that graduate students have an important role in higher education production as teaching and research assistants and role models for undergraduates. On these bases, and in the absence of student-level data, I operationalized student characteristics using seven measures:

1. Total FTE undergraduate enrollment in engineering;
2. Proportion of female engineering baccalaureates;
3. Proportion of underrepresented minority FTE undergraduate enrollment in engineering;
4. Number of full-time engineering doctoral students;

5. Proportion of underrepresented minority full-time engineering doctoral enrollment;
6. (Institution-level) Mean 75th Percentile SAT Math scores;
7. (Institution-level) Gross amount of Pell grants disbursed by the institution per FTE undergraduate enrollment.

To mitigate the extent of missing data on mean SAT math scores, I converted ACT math scores to SAT math scores wherever institutions reported only ACT scores using concordance tables provided by the College Board (Dorans, 1999).

Institutional characteristics (control variables). Berger and Milem's (2000) organizational framework, recent higher education production function studies, and STEM higher education research indicate that structural features of institutions contribute, at least indirectly, to student outcomes. Accordingly, I include five indicators of institutional characteristics:

1. Institutional control;
2. Land grant status (i.e., whether the institution is designated by its state legislature or Congress to receive the benefits of the Morrill Acts of 1862 and 1890. The original mission of these institutions included education in technical subjects such as engineering [Thelin, 2004].);
3. Selectivity;
4. Carnegie classification.
5. HBCU status; and

All institutional characteristics refer to the broader institution rather than engineering schools/colleges.

Summary of variables. Table 3.4 summarizes the variables and the sources of the variables selected to model engineering degree production in this study. In many cases, the functional form of the production models estimated included transformations of the variables in Table 3.4. Relevant procedures are discussed in the Analysis section.

Table 3.4 Variables used to model engineering degree production

Variable	Calculated?	Type	Source
<u>Outputs</u>			
Engineering bachelor's degrees per FTE undergraduate enrollment (total, URM, African American)	Yes	Continuous	ASEE
<u>Faculty Inputs (Explanatory Variables)</u>			
Proportion of FTE non-tenured/tenure-track teaching faculty in engineering	Yes	Continuous	ASEE
Proportion of FTE research faculty in engineering	Yes	Continuous	ASEE
FTE Faculty to FTE undergraduate student ratio in engineering	Yes	Continuous	ASEE
Proportion of underrepresented minority tenured/tenure-track engineering faculty	Yes	Continuous	ASEE
Proportion of female tenured/tenure-track engineering faculty	Yes	Continuous	ASEE
Expenditures for engineering research per FTE engineering undergrads	Yes	Continuous	HERD
<u>Capital Inputs (Alternative Specifications)</u>			
Expenditures for engineering research equipment per FTE engineering undergrads	Yes	Continuous	HERD
Revenues from gifts, grants and contracts, endowment earnings, etc. per FTE undergrads	Yes	Continuous	Delta Cost
<u>Other Inputs (Alternative Specifications)</u>			
Institutional expenditures for instruction	Yes	Continuous	Delta Cost
Institutional expenditures for academic support per FTE undergrad	Yes	Continuous	Delta Cost
Institutional expenditures for student services per FTE undergrad	Yes	Continuous	Delta Cost
Institutional expenditures for research per FTE undergrad	Yes	Continuous	Delta Cost
Total institutional education and general research expenditures per FTE undergrad	Yes	Continuous	Delta Cost
<u>Aggregate Student Characteristics (Control Variables)</u>			
Total FTE undergraduate enrollment in engineering	Yes	Continuous	ASEE

Table 3.4 (Cont.) Variables used to model engineering degree production.

Variable	Calculated?	Type	Source
Proportion of female engineering baccalaureates	Yes	Continuous	ASEE
Proportion of URM FTE undergraduate enrollment in engineering	Yes	Continuous	ASEE
Number of full-time engineering doctoral students	No	Continuous	ASEE
Proportion of URM full-time engineering doctoral enrollment	Yes	Continuous	ASEE
Mean 75th Percentile SAT Math scores	No	Continuous	IPEDS
Gross amount of Pell grants disbursed by institution per FTE undergrad	Yes	Continuous	Delta Cost
Institutional Characteristics (Control Variables)			
Institutional control (public/private)	No	Binary	IPEDS
Land grant status	No	Binary	IPEDS
Selectivity	Yes	Categorical	Barron's
HBCU status	No	Binary	IPEDS
Carnegie classification	Yes	Categorical	IPEDS

Analytic Methods

The research questions were addressed in four stages. First, I used multiple imputation to deal with missing data. In the second stage, I used descriptive statistics to examine trends over the period 2005 to 2011 in the outcome and explanatory variables of interest. In the third stage of analysis, I estimated fixed effects linear regression and dynamic panel models of engineering degree production by race/ethnicity. Finally, I used stochastic frontier analysis (SFA) to explore the extent to which engineering schools and colleges maximized degree production output (i.e., maximized technical efficiency) based on a production model developed in the prior stage of analysis. All data preparation (i.e., variable generation and transformation, sample selection, etc.) as well as analysis procedures were carried out in Stata/IC 12.1. Each stage of the analysis is discussed in detail below.

Missing data. In this study, missing data refers to item non-response, or missing information for some variables on some observations in my analytic sample. Multiple imputation (Allison, 2002) was used to deal with missing data among the independent variables. The degree of missing data in the analytic sample (i.e., top three quartiles of institutions conferring bachelor's degrees to underrepresented minorities) varied among these variables. Data on institutional characteristics were complete for all institutions over the entire sample period, 2005 to 2011. All of the measures drawn from the ASEE database were missing on less than 5% of the observations.

The biggest missing data challenges arose from the variables drawn from NSF's Higher Education R&D (HERD) Survey and the Delta Cost Project database. In particular, both expenditures for engineering research and equipment from the HERD survey were missing on nearly 10% of the observations. The missing data are largely due to the sampling frame of the survey, which prior to 2010 permitted a combined response from university systems with multiple campuses (e.g., University of Michigan, Pennsylvania State University, etc.). As of 2010, each campus headed by its own president or chancellor responds to the HERD survey separately (NCSES, 2013). Therefore, for 2010 and 2011, engineering research and equipment expenditures were missing on less than 4% of the observations in my sample. Institutional finance measures drawn from the Delta Cost Project database were missing on 26% to 32% of observations in the analytic sample. This large amount of missing data arises because the Delta Cost database currently includes data up to 2010, which is one year shy of my sample period. Considering instead the period from 2005 to 2010, the variables drawn from Delta Cost were missing on 8% to 13% of observations. Therefore, the alternative model specifications that include institutional finance variables from Delta Cost restrict the sample period to 2005 to 2010.

Missing data estimation. Once the "dirty little secret of statistics," these days the ubiquitous problem of missing data in social science research can be addressed through a number of approaches (Allison, 2009, p. 72). Justification for using a particular approach starts with an assumption about how the data came to be missing. The strongest assumption is that data are missing completely at random (MCAR). For my study, the

MCAR assumption would imply that the probability that a particular variable is missing for a particular (institution-year) observation does not depend on the value of *any* variables in my production model (Allison, 2009). My approach to dealing with missing data is based on a weaker, but still strong, assumption that the data are missing at random (MAR). This assumption implies that the probability that a variable is missing for a particular observation does not depend on the value of that variable itself, after controlling for the other explanatory and control variables in the production model. Allison (2002, 2009) describes two broad approaches for dealing with MAR data that have potentially excellent statistical properties: maximum likelihood and multiple imputation. I chose multiple imputation because it can be implemented in a number of conventional statistical packages, and applying it to panel data is fairly straight forward in Stata 12.1.

In general, multiple imputation methods use available data to estimate regression models for each variable with missing data, and a random draw from the simulated error distribution for each regression model is added to produce the imputed values. This method is used to create several imputed data sets, but the imputed values across the data sets will differ because the random components differ. Thus, the model of interest is estimated for each imputed data set, the parameter (coefficient) estimates are averaged across the data sets, and the variability across the estimates corrects the standard errors (Allison, 2010).

For this study, the Stata 12.1 command `mi impute mvn` was used to create imputed data sets. Using data augmentation – an iterative Markov Chain Monte Carlo

(MCMC) procedure – `mi impute mvn` generates imputed values for one or more continuous variables assuming an underlying multivariate normal model. In my study, starting values for the MCMC procedure were obtained based on the means and covariance matrix estimated via the Expectation Maximization (EM) algorithm (Allison, 2002; Stata, 2011). Since the multivariate normal model assumes that all imputation variables have a normal distribution, logarithmic transformations of some highly (positively) skewed variables were imputed. Autocorrelation plots of the Worst Linear Function were used to assess MCMC convergence (Stata, 2011).

Given the large number of potential imputation variables relative to the number of institution-year observations in my sample, the MCMC procedure would not converge with all of my variables included in the multiple imputation model. Therefore, rather than estimating one imputation model that included all the variables (i.e., generating data sets that included imputations for every possible variable), I took an on-demand approach to the imputation process. I estimated separate imputation models at different stages of the analysis to limit the number of imputation variables. For example, for engineering degree production functions that included faculty inputs but not capital or institutional inputs, I estimated an imputation model that generated imputed values only for faculty input and control variables, and not for capital or institutional input variables.

Research question #1: Trends in engineering degree output and faculty inputs. In the second stage of the analysis, I compiled descriptive statistics for the variables used in the analysis over all institution-year observations. To broadly assess overall variation in the outcome and explanatory variables of interest, I specifically considered the seven-year (2005 to 2011) change in engineering bachelor's degrees by student race/ethnicity, proportion of non-tenured/tenure-track teaching faculty, faculty-to-student ratio, gender and racial/ethnic composition of tenured and tenure-track faculty, and engineering research expenditures across multiple institutional contexts.

A prerequisite for the fixed effects linear regression models used to address Research Question #2 is that the outcome and explanatory variables change over time (Allison, 2009). Therefore, I also examined within-institution variation by considering decomposed statistics for the outcome and explanatory variables. That is, each variable (x_{it}) was decomposed to provide overall, between-institution, and within-institution information. Overall information refers to the overall mean, $\bar{\bar{x}}$, or variation over all institution-year observations. Between-institution information refers to panel level means, $\bar{x}_i$, or variation between each institution's seven-year mean. And within-institution information refers to the variable variation relative to the overall mean, $x_{it} - \bar{x}_i + \bar{\bar{x}}$ (Garcia & Stewart, 2012). Non-zero standard deviations for the within portion of the variables provided evidence that variables changed over time within institutions.

Research question #2: Estimating an engineering degree production function. The third stage of the analysis involved specification and estimation of three sets of panel data models to test whether the relationships between engineering bachelor's degree output and engineering school/college inputs differed by student race/ethnicity. Before detailing these steps, however, I present some background on panel data, fixed effects linear regression models, and dynamic panel models in order to provide the basis for my model estimation strategy.

Panel data. Because cross-sectional studies involve multiple units (institutions, students, etc.) observed at a single point in time, traditional regression analyses drawing on cross-sectional data rely on variations between units to infer relationships among the predictors and outcomes (Zhang, 2010). The only way to statistically "control" for potential differences between units that might affect the outcome is to measure them and put them in the model. This approach opens the door to the classic problem of omitted variable bias or unobserved unit heterogeneity, which can easily undermine even the most meticulous analyses (Allison, 2009).

This study utilizes longitudinal or panel data in which multiple units – engineering schools – are observed at multiple points in time. When paired with appropriate statistical methods, panel data offer at least three advantages over cross-sectional data that are pertinent to the goals of this study. First, because panel data are two dimensional (i.e., involving multiple units and multiple time points), they usually contain additional useful information, greater sample variability, and more degrees of freedom. These advantages improve the statistical efficiency of the estimates (Hsiao, 2007). Second, when appropriately applied, panel methods can control for unobserved between-unit heterogeneity, which Zhang (2010) contends is their main "statistical attraction" for higher education policy studies (p. 308). In particular, fixed effects regression models (one of many panel methods) can control for institution effects that do not change over time (Allison, 2009). Third, panel models are conceptually appealing given their attention to within-unit variation (Zhang, 2010). For example, a cross-section of engineering schools for, say, 2005, enables me to examine the extent to which differences between institutions' faculty inputs in 2005 explain why some institutions had higher or lower than average engineering degree output in that year. Focusing on within-unit variation enables me to directly test the relationship between changes in faculty inputs and changes in degree output. That is, are changes in faculty inputs related to changes in degree output?

Fixed effects linear regression models. Two common methods for estimating linear regression models using panel data are fixed effects (FE) and random effects (RE) estimation. These panel models take the form

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \beta_k x_{itk} + \alpha_i + \varepsilon_{it}, \tag{3.1}$$

where the outcome y for the i-th unit at time t is determined by k different predictors observed for each unit at each time point. The disturbance (or random error) term, ε_{it}, is also different for each unit at each time period. However, the slope coefficients, β_k, and the term α_i are assumed to be constant over time (i.e., they do not have a t subscript) (Allision, 2009; Woolridge, 2009). The term α_i goes by many names, including the "unobserved effect" (Woolridge, 2009), "unobserved heterogeneity" or "unit heterogeneity" (Allison, 2010), and "fixed effect" (Woolridge, 2009; Zhang, 2010) to name a few; what is most important is that α_i represents the combined effect on y of all unobserved variables that are constant over time (Allison, 2009; Woolridge, 2009).

The choice of whether to use RE or FE methods to estimate the model represented by Equation 3.1 is determined by the assumed relationship between α_i and x_{it} (Woolridge, 2009). Random effects estimation is based on the assumption that α_i is uncorrelated with all the independent variables, whereas fixed effects estimation allows for arbitrary correlation between α_i and x_{it}. I chose a fixed effects approach because as Zhang (2010) notes, "in many scenarios in higher education research, there are strong reasons to believe that the individual-specific effects are correlated with explanatory variables" (p. 319). With respect to my seven-year study, unobserved, time-invariant effects, α_i might include such measures as geographic location of an engineering school, institutional prestige, or presence of a minority engineering retention program, all of which could conceivably correlate with the sets of faculty inputs, student characteristics, or institutional characteristics that were specified as independent variables.

In practice, i.e., in Stata and other statistical packages, the FE method estimates Equation 3.1 by first averaging Equation 3.1 over time for each institution i,

$$\bar{y}_i = \beta_0 + \beta_1\bar{x}_{i1} + \beta_2\bar{x}_{i2} + \cdots + \beta_k\bar{x}_{ik} + \alpha_i + \bar{\varepsilon}_i, \tag{3.2}$$

then subtracting Equation 3.2 from Equation 3.1 to get,

$$y_{it} - \bar{y}_i = \beta_1(x_{it1} - \bar{x}_{i1}) + \cdots + \beta_k(x_{itk} - \bar{x}_{ik}) + (\varepsilon_{it} - \bar{\varepsilon}_i), \ \ or \tag{3.3}$$

$$y^*_{it} = \beta_1 x^*_{it1} + \cdots + \beta_k x^*_{itk} + \varepsilon^*_{it}, \tag{3.4}$$

Where, $y^*_{it} = y_{it} - \bar{y}_i$, etc. Through this procedure α_i is eliminated. In other words, the combined effect on y of all unobserved variables that are constant over time gets subtracted out. This is called the *fixed effects transformation* or *within transformation* (Woolridge, 2009). Next, y^* is regressed on x^* as usual, and the coefficient estimates obtained are called fixed effects estimators or within estimators. The fixed effects transformation effectively controls for all time-invariant predictors (measured or unmeasured) that may differ between institutions because Equation 3.4 uses variation within units rather than between units to estimate the coefficients (Allison, 2009; Zhang, 2010).

FE models control for the effects of unobserved predictors that are constant over time but do not control for unobserved predictors that change over time. Therefore, the potential for omitted variables bias is reduced with fixed effects estimation but not eliminated. There are also disadvantages to using fixed effects rather than random effects models. Estimating the “direct” effect of time-invariant predictors like gender or HBCU status can only be done with random effects models. Random effects models produce more efficient estimates (smaller standard errors) compared to FE models. However, FE estimates are less prone to bias (Allison, 2009). Statistical tests (i.e., the Hausman test, the Mundlak test) have been developed that compare RE and FE models in order to address these modeling trade-offs (Garcia & Stewart, 2012).

Woolridge (2009) argues that, “FE is almost always much more convincing than RE for policy analysis using aggregated data” (p. 493). But the following assumptions must also be met for FE coefficient estimates to be unbiased:

1. Each predictor variable changes overtime (for at least some units *i*), and there is no perfect linear relationship among any predictors.

2. The random errors, ε_{it}, have the same variance given any value of the of the predictor variables for all time periods (i.e., homoskedasticity).
3. There is no correlation between errors, ε_{it}, in different time periods (i.e., errors are serially uncorrelated).
4. Strict exogeneity on the predictor variables. That means that the predictor variables are statistically independent of the random error term, ε_{it}, for any time t.

My analysis procedures, which are discussed later, included steps to address Assumptions #1, 2, and 3 in the fixed effects framework. In order to address potential violation of Assumption 4, I used a dynamic panel model.

Dynamic panel models. Allison (2009) notes that Assumption #4 – that the predictor variables, $\mathbf{x}_{it}$, are statistically independent of the random error term, ε_i, at any time period – can be violated if "$\mathbf{x}_{it}$ is affected by y at an earlier point in time or if one component of $\mathbf{x}_{it}$ is y itself at an earlier point in time" (p. 94). The latter scenario implies that at least one lag of the dependent variable is included among the predictors. The basic panel model becomes,

$$y_{it} = \delta y_{it-1} + \beta_1 x_{it1} + \cdots + \beta_k x_{itk} + \alpha_i + \varepsilon_{it}, \tag{3.5}$$

where y_{it-1} is now thought to predict y_{it}. Panel models that include lagged dependent variables as predictors, as in Equation 3.5, are *dynamic model*s (Allison, 2009). Many social science issues might be considered dynamic: dynamic wage equations (i.e., wage in one period is related to wage in the previous period); dynamic employment models (employment status in one period is related to employment in the previous period) (StataCorp, 2011). Titus (2009) showed that states' bachelor's degree production inefficiency was also dynamic in nature. With respect to my study, it might be plausible that the outcome degrees awarded per FTE in 2011was related to degrees per FTE in 2010, for example.

Estimating Equation 3.5 starts much like estimating 3.1. However, instead of using the within transformation ($y_{it}^{*} = y_{it} - \bar{y}_i$, etc) I use the first difference transformation to eliminate α_i as follows,

$$y_{it} - y_{it-1} = \delta(y_{it-1} - y_{it-2}) + \beta_1(x_{it,1} - x_{it-1,1}) + \cdots + \beta_k(x_{it,k} - x_{it-1,k}) + (\varepsilon_{it} - \varepsilon_{it-1}) \tag{3.6}$$

$$\Delta y_i = \delta \Delta y_{it-1} + \beta_1 \Delta x_{i,1} + \cdots + \beta_k \Delta x_{i,k} + \Delta\varepsilon_i \tag{3.7}$$

Equation 3.7 clearly violates the exogeneity assumption because, by construction, the predictor Δy_{it-1} is correlated with the error term $\Delta\varepsilon_i$ because y_{it-1} is correlated with ε_{it-1}, violating the strict exogeneity assumption (Woolridge, 2009). Thus, y_{it-1} is an endogenous variable, and least squares coefficient estimates for endogenous variables are biased and inconsistent (Woolridge, 2009). Therefore, basic panel estimation methods cannot be used to estimate Equation 3.7. Instead, econometric approaches using generalized method of moments (GMM) and instrumental variables have been developed to estimate dynamic models (Allison, 2009). Perhaps the most popular approach is that of Arellano and Bond (1991). The Arellano-Bond estimator starts by transforming all the predictors to eliminate α_i– usually by first differencing as in Equation 3.6 – and uses GMM with instrumental variables to estimate the coefficients. The Arellano-Bond estimator uses all past information on y_{it} (i.e., the full set of available lags) as instruments for the lagged dependent variable (Arellano & Bond, 1991).

Model specification and estimation. To address Research Question #2, I specified three sets of panel data models to test whether the relationships between engineering bachelor's degree output and engineering school/college inputs differed by student race/ethnicity. First, baseline fixed effects regression models were specified to examine potential differences by race/ethnicity in the role of faculty inputs. Second, alternative fixed effects models were specified to consider the role of capital inputs and broader institutional expenditures. Third, a dynamic model was specified to relax the exogeneity assumption of basic fixed effects regression. These models and the procedures used to estimate them are discussed next.

Baseline FE models. To address Research Question #2, I specified a logarithmic functional form of Equation 3.1. In vector notation and substituting my outcome and predictor variables, the model becomes,

$$\ln\left(\frac{degrees}{FTE}\right)_{it} = \beta\,\mathbf{F}_{it} + \gamma\mathbf{S}_{it} + \alpha_i + \varepsilon_{it}, \tag{3.8}$$

where the outcome is the natural log of engineering bachelor's degrees per FTE engineering undergraduate of enrollment; **F** contains the faculty inputs listed in Table 3.4, including the natural log of engineering research expenditures per FTE; and **S** contains the student characteristics listed in Table 3.4, including the natural logs of total FTE engineering undergraduate enrollment and number of full-time engineering doctoral students. I used logarithmic transformations for three reasons: 1) to allow for nonlinear relationships between the outcome and explanatory variables; 2) to narrow the ranges of the variables of interest, making the coefficient estimates less sensitive to extreme observations; and 3) to allow for more meaningful interpretations of the coefficient estimates. In particular, following Woolridge's (2009) rules of thumb, the natural log is often applied to large positive integer values such as dollar amounts, number of employees, school enrollment, etc.; the natural log is sometimes used to transform proportion or percentage variables as well. Histograms presented in Figures A.1 and A.2 of the appendix provide graphical displays of the distribution of log transformed variables, before and after applying the transformation.

Fixed effects linear regression was used to estimate Equation 3.8 by race/ethnicity by specifying three different outcomes: engineering bachelor's degrees to all students per FTE undergraduate engineering enrollment of all students; engineering bachelor's degrees to underrepresented minorities per FTE undergraduate engineering enrollment of underrepresented minorities; and engineering bachelor's degrees to African Americans per FTE undergraduate engineering enrollment of African Americans. Recognizing that the outcomes could change either because FTE enrollment or number of degrees awarded by race/ethnicity changes, I used the basic logarithm rule that $\ln(\frac{degrees}{FTE}) = \ln degrees - \ln FTE$ to rewrite Equation 3.8 as

$$\ln\,(degrees_{race})_{it} = \beta\,\mathbf{F}_{it} + \gamma\mathbf{S}_{it} + \ln(FTE_{race})_{it} + \alpha_i + \varepsilon_{it}, \qquad (3.9)$$

$$\ln\,(degrees_{race})_{it} = \beta\,\mathbf{F}_{it} + \gamma\mathbf{S}_{it} + \alpha_i + \varepsilon_{it}, \qquad (3.10)$$

where the $\ln(FTE_{race})$ term that appears in Equation 3.9 is folded into the set of student characteristics, **S**, in Equation 3.10. This procedure allowed me to not only account for the fact that engineering schools with large numbers of URMs, for example, will award more degrees to URMs, it also allowed me to directly estimate this ‘enrollment effect.’ In addition to estimating Equation 3.10 by race/ethnicity, similar to Zhang (2009), I stratified the samples to examine how the relationship between faculty inputs and degree output for these student groups varied across different institutional contexts. Specifically, I estimated separate fixed effects models by institutional control, Carnegie classification, institutional selectivity, and HBCU status. Equation 3.10 can be thought of as my baseline model – the model of primary interest in the study from which alternative model specifications were derived.

Alternative inputs FE models. To test whether selected measures of capital predicted engineering degree output by race ethnicity (Research Question #2a), I estimated Equation 3.10 replacing the set of faculty inputs with the set of capital inputs, **C**, listed in Table 3.4,

$$\ln\,(degrees_{race})_{it} = \theta\,\mathbf{C}_{it} + \gamma\mathbf{S}_{it} + \alpha_i + \varepsilon_{it}, \qquad (3.11)$$

Then I estimated the model with both capital and faculty inputs,

$$\ln\,(degrees_{race})_{it} = \beta\,\mathbf{F}_{it} + \theta\,\mathbf{C}_{it} + \gamma\mathbf{S}_{it} + \alpha_i + \varepsilon_{it}, \qquad (3.12)$$

I used a similar approach to test whether selected institutional expenditure measures predicted engineering degree output (Research Question #2b). Specifically, I estimated Equation 3.10 including the set of institutional expenditures, **E**, listed in Table 3.4,

$$\ln\,(degrees_{race})_{it} = \beta\,\mathbf{F}_{it} + \gamma\mathbf{S}_{it} + \pi\mathbf{E}_{it} + \alpha_i + \varepsilon_{it}, \qquad (3.13)$$

Estimation procedures for FE models. The Stata command `xtreg` with the `fe` option was used to estimate the baseline and alternative inputs models. The `xtreg` option `vce(robust)`, which produces robust standard errors, was used to adjust for potential heteroskedasticity or within-panel serial correlation in the random error term, ε_{it} (Garcia & Stewart, 2012). I prefixed these estimation commands with `mi estimate` in order to fit the models separately on each of the twenty imputed data sets, pool the results, and adjust the coefficients and standard errors for the variability between imputations (StataCorp, 2011).

Dynamic model. To relax the exogeneity assumption of basic fixed effects regression and examine the extent to which estimates differed when controlling for past degree output (Research Question #2c), I specified a dynamic panel model that included one lag of the dependent variable as a predictor,

$$\ln\left(degrees_{race}\right)_{it} = \delta \ln\left(degrees_{race}\right)_{it-1} + \beta\, \mathbf{F}_{it} + \gamma \mathbf{S}_{it} + \alpha_i + \varepsilon_{it}. \quad (3.14)$$

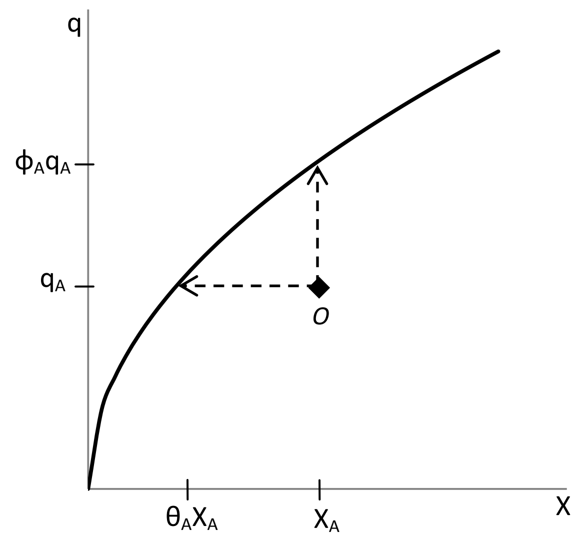
For the dynamic model, I used the Arellano-Bond GMM estimator via the Stata command `xtabond`. This procedure combined panel data transformations with instrumental variables techniques to address endogeneity. The option `vce(robust)` was used to adjust for potential heteroskedasticity. The `xtabond` estimators require that the random error, ε_{it}, be serially uncorrelated. Woolridge (2009) notes that assuming no serial correlation is equivalent to assuming that only one lag of the dependent variable appears in the model. Therefore, to test this assumption, I used the command `estat` `abond` to evaluate the results of the Arellano-Bond test for serial correlation after estimating each dynamic model.

Research question #3: Assessing degree production efficiency. The fourth stage of the analysis was an exploratory efficiency assessment, which is arguably a necessary step in estimating a "production function" in the strict economic sense. This section explains the motivation for this stage of the analysis, the method chosen to estimate (*in*)efficiency, and the Stata procedures that were used.

Production frontiers. Estimating production functions from observed data is fairly standard practice in econometrics. Fundamental to these analyses is the assumption that a production function represents what Greene (2007) characterizes as the "ideal," the maximum output possible from a given set of inputs. This ideal or maximum level of production is defined as the *production frontier*. Estimations of *technical efficiency*[5] uncover to the extent to which the observed behavior of firms reaches (or falls short of) the ideal level of production (Greene, 2007). Technical efficiency can be represented by the distance from the observed behavior of a firm to the production frontier given a set of inputs. This is illustrated in Figure 3.1. The hypothetical production frontier shows output, q, as a function of input vectors, x. The data point (x_A, q_A) represents the observed behavior of firm O given x_A set of inputs. The figure shows that firm O can increase technical efficiency by reducing inputs (to $\theta_A x_A$) to produce the same output (q_A) or by increasing output (to $\phi_A q_A$) using the same inputs (Greene, 2007).

[5] Other efficiencies that have been estimated in higher education studies include *allocative*, *scale*, and *economic* or *overall* efficiency (see Salerno [2002, 2003] for a review).

Figure 3.1 Measures of technical efficiency



Source: Greene, 2007

The notion that there exists some theoretically ideal production level, i.e. production frontier, comes from the producer theory-based expectation of optimal firm decisions, in which firms try to maximize profits through decisions about the right mix of inputs to achieve a desired output. Yet, some (perhaps many) might reasonably argue that concepts like ‘output maximization’ or ‘efficient production’ are inappropriate for higher education institutions given their unique qualities (Stanford News Service, 1995; Lewis and Dundar, 2001). Likewise, the higher education production function is essentially a “black box”; we do not explicitly know the inputs and process necessary to produce maximum outputs, which we also cannot specify definitively (Lewis & Dundar, 2001). Hopkins (1990) explains,

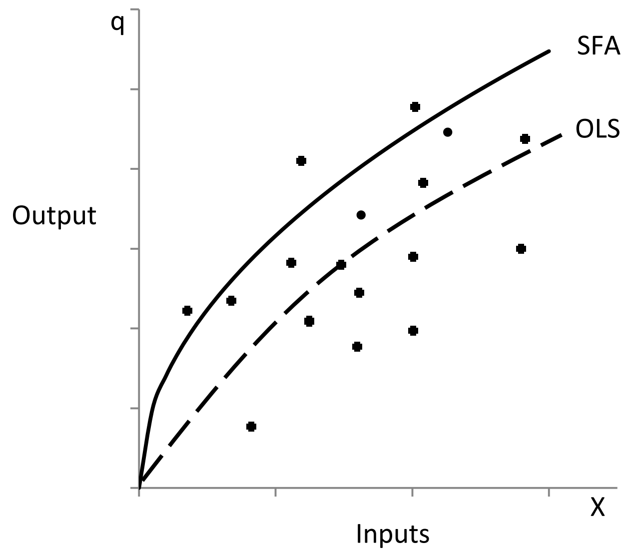
> …there is no reason to believe that the educational enterprise has been operating on the efficient frontier of production possibilities; and there are many reasons to believe that it has not. This means that even if we were able to specify the true and complete functional form, we would still be

> unable to estimate the true coefficients of the model from any existing set of data. (p. 13)

Perhaps understandably then, most (higher) education production function studies make no attempt to assess technical efficiency (for example, Dolan & Schmidt, 1994; Wolf-Wendel, Baker, & Morphew, 2000; Hubbard & Stage, 2010; Ostreko, 2012). In fact, without a known production function, it is impossible to estimate technical efficiency in absolute terms. Nevertheless, a few recent institution-level production function studies use stochastic frontier analysis (SFA) to tease out relative inefficiency from standard regression estimates (Blose, Porter, & Kokkelenberg, 2006; Eagan, 2010; Webber & Ehrenberg, 2010).

Stochastic frontier analysis. Frontier production functions are basically familiar regression models that have been modified to reflect the theoretical premise that firms cannot exceed the ideal output and deviations from the ideal are due to inefficiency (Greene, 2007). This is depicted graphically in Figure 3.2. Standard regression models of higher education production trace out the average behavior of institutions (dashed line labeled “OLS” in Figure 3.2). By design, observations lay above and below the regression line, but in a production function framework this implies that institutions above the line exceed the maximum attainable output. On the other hand, stochastic frontier estimators approximately trace the observed production frontier, i.e., maximum-output observations, and account for random error (i.e., measurement error and random noise) as well as inefficiency. In Figure 3.2, observations that exceed the observed frontier (line labeled “SFA”) are attributable to random error. Observations below the frontier are due to some combination of random error and technical inefficiency.

Figure 3.2 Traditional and stochastic frontier production functions.



Stochastic frontier analysis, which was developed simultaneously by Aigner, Lovell, and Schmidt (1977) and Messuen and van der Broeck (1977), is now the standard method for econometric analysis of technical efficiency (Kumbhakar & Lovell, 2000; Greene, 2007). Efficiency analysis via SFA is essentially an analysis of the residuals from the production model. Mathematically, stochastic frontier analysis extends traditional regression models by decomposing the familiar random error term into an error term (v) and an inefficiency term (u). For panel data, with output y for the i-th institution at time t, given a vector of k inputs x, SFA models of the form,

$$y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{jit} + \varepsilon_{it}, \tag{3.15}$$

$$\varepsilon_{it} = v_{it} - u_{it}. \tag{3.16}$$

The random error term, v_{it}, is assumed to have a symmetric distribution and to be independent (i.e., uncorrelated with the predictors, x_{jit}). Technical inefficiency, u_{it}, is strictly nonnegative and is assumed to have a half normal distribution and be uncorrelated with v_{it} and x. The complete derivation of panel data production frontier models is provided in Kumhakar and Lovell (2000). In practice, particularly in Stata, the SFA production model uses a log-log functional form. Therefore, substituting the variables and notation from my earlier analyses, my SFA engineering degree production model is

$$\ln degrees = \beta \ln \mathbf{F}_{\mathrm{it}} + \gamma \ln \mathbf{S} + v_{it} - u_{it} \, . \tag{3.17}$$

I used this model to generate inefficiency scores based on u_{it} for each engineering school/college in the production of bachelor's degrees. I considered both time-invariant and time-varying inefficiency estimates using the Stata command `xtfrontier`. Time-invariant inefficiency ($u_{it} = u_i$) suggests that inefficiency was constant within institutions over the 7 year sample period. The time-varying case allowed for a unique inefficiency score for each institution in each year. Since the Stata command `xtfrontier` provided estimates for a log-log linear production frontier model, logarithmic transformations of the data were necessary before estimation (StataCorp, 2011).

Multiple comparisons. Because this study involved estimating and comparing degree production models across multiple student subgroups and multiple institutional settings, the classical statistical problem of multiple comparisons (i.e. multiple testing) might be a fair concern. The main problem with multiple testing is that the probability of detecting a statistically significant relationship when there is not one (i.e., false positives or Type I errors) increases with each additional test (Schochet, 2008; Gelman, Hill, & Yajima, 2012). That is, since the statistical significance level chosen also indicates the acceptable Type I error rate, a significance level of $\alpha = .05$ indicates that I would expect to incorrectly detect a statistically significant relationship only 5% of the time. However, if I consider or compare multiple models together, the combined Type 1 error rate will exceed the 5% threshold (Schochet, 2008).

There are many methods for dealing with multiple comparisons. Most traditional methods rely on adjusting the p-values at which the statistical significance of the estimates are evaluated. For example, the Bonferonni method divides p-values by the number of hypothesis tests/models estimated (Schochet, 2008). Although such methods reduce the Type I error rate, they also reduce statistical power and increase the probability of not detecting true relationships (Type II error). A technical methods report of the U.S. Department of Education's Institute for Education Sciences explains, "There is disagreement about the use of multiple testing procedures and the appropriate tradeoff between Type I error and statistical power" (Schochet, 2008, p.1) but offers practical guidelines for addressing the problem in evaluations of educational interventions.

In this study, I decided not to formally adjust for Type I error or multiple comparisons. The analyses conducted are not designed to prove conclusive evidence of the effect of faculty predictors on engineering degree output but rather provide preliminary information and insights about these relationships. Accordingly, IES advises that multiple testing procedures are not required for such exploratory analyses (Schochet, 2008). However, I have attempted to manage expectations regarding my findings by including notes in my results tables (Chapter 4) to indicate the increased likelihood of Type I errors, given my statistical significance level of $\alpha = .05$

At the same time, recent research by Gelman, Hill, and Yajima (2012) suggests that the real problem is not multiple testing/comparisons at all but insufficient modeling of the relationships of interest. In their article entitled, "Why We (Usually) Don't Have to Worry about Multiple Comparisons," Gelman and others (2012) argue that testing the null hypothesis that no relationships exist is an unhelpful proposition to begin with. For example, in the context of my study, there is no reason to believe that there are no relationships whatsoever between faculty predictors and engineering bachelor's degree output. In fact, I have conducted the study precisely because there are some indications from available research that these relationships do exist. Similarly, there is evidence to suggest that there may be differences across student subgroups and institutional contexts. Therefore, Gelman, Hill, and Yajima (2012) suggest focusing on more appropriate statistical modeling techniques rather than multiple comparisons adjustments.

Limitations

The research design is limited with respect to both the data and analysis methods used. With respect to data, the primary source for this study, ASEE's Survey of Engineering and Engineering Technology Colleges, is neither a census nor a random sample of ABET-accredited engineering schools. Therefore, the findings from the study may not be representative of all programs. For example, only 12 out of 16 ABET-accredited HBCU engineering schools are included in the ASEE data set. Nevertheless, high participation rates among all institutions (92% of all eligible institutions are represented) help to mitigate this general limitation. Also, unlike data drawn from the National Science Foundation or the U.S. Department of Education, the ASEE data are not subject to clear quality standards and quality control procedures.

Financial data are also inherently limited for multi-institution comparisons, as discussed in Chapter 2. In particular, expenditures may not be comparable across institutions depending on institutional accounting and reporting practices. According to an IPEDS official, the largest discrepancies between institutions come from accounting differences between public and private institutions (GASB vs. FASB institutions) (C. Lenihan, personal communication, February 14, 2013). The use of Delta Cost Project data directly addresses this issue since these data are specifically translated to allow for such comparisons. Nevertheless, the IPEDS official also noted that despite instructions, definitions, and support provided by IPEDS, "The tough part of all of this is that there is no way of knowing what institutions are counting in different expense categories to indicate if there are any adjustments that should be made to the data" (personal communication, February 14, 2013). The official also advised that the best comparisons would be among similar institutions, for example, Carnegie classification or other institutional groupings. As described earlier in this chapter, this recommended strategy was used throughout the study.

Another key limitation of the study is its use of data on broader institutional characteristics as proxies for the engineering schools. Unfortunately program-level expenditures, student SAT Math scores, Pell grants, etc. were not available. However, these measures were included only in alternative models that were not central to the study.

With respect to the analysis, in addition to the problem of multiple comparisons, the main limitation is the potential for omitted variables bias. The "true" engineering production function, like the broader higher education production function is essentially a black box. There is no way specifying inputs conclusively, so the potential for omitting a potentially significant input remains. The estimation of fixed effects models diminishes the problem, but there are likely unobserved variables that change over time, which FE cannot address.

For example, colleges and universities routinely operate and/or support STEM programmatic interventions designed to foster collaborative learning environments and facilitate positive interactions with faculty and peers – such as minority freshmen orientation, clustering, and structured study groups (Reichert & Absher, 1997); peer mentoring programs (Astin & Astin, 1992; Good, Haplin, & Haplin, 2000); and student-chapter professional organizations (Jackson, Gardner, & Sullivan, 1993; Reichert & Absher, 1997; Chang, Cerna, Han, & Saenz, 2008; Hurtado et al., 2007). Available empirical research is largely suggestive of positive effects on a range of student outcomes in STEM as a result of participation in summer bridge programs (Evans, 1999; Ami, 2001; Ohland & Zhang, 2002; Walpole et al., 2008; Zhe, Doverspike, Zhao, Lam, &

Menzemer, 2010); undergraduate research programs (Nagda et al., 1998; Kardash, 2000; Zydney, Bennett, Shahid, & Bauer, 2002; Bauer & Bennett, 2003; Barlow & Villarejo, 2004; Lopatto, 2004, 2007; Hurtado et al., 2007; Hurtado, et al., 2008; Laursen et al., 2010); and comprehensive retention programs like the Meyerhoff Scholars Program (Hrabowski & Maton, 1995; Fries-Britt, 1998; Maton, Hrabowski, Schmitt, 2000; Maton & Hrabowski, 2004; Summers & Hrabowski, 2006; Carter, Mandell, & Maton, 2009) and programs falling under the Minority Engineering Program (MEP) umbrella (Treisman, 1985; Landis, 1988; Ohland & Zhang, 2002; Good, Haplin, & Haplin, 2002; May & Chubin, 2003; Tsui, 2007). Thus, the potential availability of these types of interventions within the engineering schools/colleges included in my study might confound my results, since no measures were available to capture this input. Other potential confounders include: expenditures for instruction and academic support specifically for engineering schools and colleges; special curricula; the availability of dual degree partnerships with other institutions; and admissions and enrollment rates in engineering.

Finally, this study is discipline-specific only with respect to the broad notion of "STEM"; I do not consider the disciplinary heterogeneity within engineering. Similarly, the study does not fully disaggregate "underrepresented minorities." That is, I do not consider outcomes for Latino or Native American students separately, nor do I consider potential gender differences within or across racial/ethnic groups.

CHAPTER 4 – FINDINGS

The central objective of this study was to estimate an engineering bachelor's degree production function, with particular attention to possible differential effects of faculty inputs on degree output by student race/ethnicity and institutional context. To accomplish this goal, I analyzed descriptive statistics and trends in engineering degree output by race/ethnicity and faculty inputs over the sample period, 2005 to 2011, and across different institutional contexts. I estimated fixed effects linear regression degree production models to examine the relationship between faculty inputs and degree output and specified alternative models to explore the effects of capital and institutional inputs. I also estimated a dynamic panel model to compare against the basic fixed effects degree production model. Finally, I used stochastic frontier analysis (SFA) to explore the degree to which the engineering schools/colleges in my sample had maximized degree output based on my production model. The results of these analyses are presented in this chapter.

Research Question #1: Trends in Engineering Degree Output and Faculty Inputs

Before estimating panel data models of engineering degree production, I examined descriptive statistics to understand how the outcome and explanatory variables changed over the sample period and within different institutional contexts. Table 4.1 presents overall descriptive statistics for all the variables used in the study. On average, the engineering schools and colleges in the sample awarded 249 bachelor's degrees per year during 2005 to 2011, with 28 degrees going to underrepresented minorities and 11 to Blacks specifically. The faculty to student ratio in engineering schools averaged 1:10. The average share of non-tenured/tenure-track members of the teaching faculty was 14%, and the tenured and tenure-track faculty were 6% underrepresented minority, 3% Black, and 13% female. Research faculty constituted 9% of the entire engineering faculty and an average of $14,000 was spent on engineering research for every FTE engineering undergraduate.

On average, the engineering schools in the sample enrolled 1380 FTE undergraduates, 15% and 7% of whom were underrepresented minorities and African Americans, respectively. The schools also enrolled an average of 176 full-time Ph.D. students, who were 3% URM and 2% Black.

Among the 324 institutions in the sample, 63% were public, 37% were private, 19% were land grant institutions, and 3% were HBCUs. With respect to institutional selectivity, 28% of the institutions in the sample were most competitive or highly competitive, 24% were very competitive, 38% were competitive, and 10% were less competitive or noncompetitive, according to Barron's competitiveness index. Also, the majority of the institutions in the sample, 58%, were doctorate or research institutions, 31% were master's institutions, just under 10% were bachelor's institutions, and only 5 institutions (close to 2%) were special schools of engineering according to the 2010 basic Carnegie classifications.

Table 4.1 Descriptive Statistics for all variables used in the study. (Calculated over all institution-year observations)

Variable	N	Mean	Std. Dev.	Min	Max
Engineering Bachelor's Degrees					
to all student	2266	249	264	1	1950
to URM students	2221	28	40	0	414
to Black students	2221	11	19	0	206
Faculty Inputs					
Proportion non-TTT faculty	2191	0.14	0.14	0	0.91
Proportion research faculty	2191	0.09	0.13	0	0.80
Faculty-student ratio	2169	0.10	0.11	0.01	1.60
Proportion URM faculty	2137	0.06	0.08	0	1
Proportion Black faculty	2137	0.03	0.07	0	1
Proportion female faculty	2191	0.13	0.08	0	0.67
Engr. research exp per engr. FTE	1899	14,292	30,482	0	479,492
Alternative Inputs					
Engr. equipment exp per FTE	1899	896	2186	0	48,717
Endowment/gift revenue per FTE	1793	8691	44,784	-594,815	516,393
Inst. instructional exp per FTE	1802	13,042	12,341	2465	109,681
Inst. academic sup exp per FTE	1802	3471	4146	13	36,801
Inst. student sup exp per FTE	1802	2456	2464	141	26,538
Inst. research exp per FTE	1636	6953	12,874	3	135,395
Education & related exp per FTE	1802	23,491	21,115	5436	330,050
Student Characteristics					
Total engr. undergrad FTE	2241	1380	1379	12	8990
URM engr. undergrad FTE	2177	201	271	0	2364
Black engr. undergrad FTE	2177	81	128	0	1366
Prop. female engr. B.S.	2266	0.17	0.09	0	1
Prop. URM engr. undergrad	2177	0.15	0.16	0	0.98
Prop. Black engr. undergrad	2177	0.07	0.14	0	0.98
Engr. PhD students	2268	176	324	0	2263
Prop. URM engr. PhD	2225	0.03	0.06	0	0.50
Prop. Black engr. PhD	2225	0.02	0.05	0	0.50
Avg. SAT-Math scores	2172	633	68	440	800
Pell grant dollars per FTE	1767	742	470	22	3443

Table 4.1 (Cont.) Descriptive Statistics for all variables used in the study. (Calculated over all institution-year observations)

Variable	N	Mean	Std. Dev.	Min	Max
Institutional Characteristics					
Public	2268	0.63	0.48	0	1
Land grant	2268	0.19	0.39	0	1
Selectivity	2268	2.29	0.98	1	4
Carnegie classification	2268	1.56	0.76	1	5
HBCU	2268	0.03	0.17	0	1

Source: Analysis of data from the ASEE Annual Survey of Engineering and Engineering Technology Colleges, the NSF Higher Education R&D Survey, IPEDS, the Delta Cost Project Database, and Barron's Profiles of American Colleges.

Table 4.2 presents information on how bachelor's degrees by race/ethnicity and faculty inputs varied from 2005 to 2011 across all institutions in the sample. The total number of engineering bachelor's degrees awarded each year increased 10% across the sample. The annual number of engineering bachelor's degrees earned by URMs increased 18%, but the number of degree degrees earned by Black students specifically dropped 10% during the sample period, which is consistent with the regressive trends discussed in Chapter 1.

The share of non-tenured/tenure-track teaching faculty increased 8% during the sample period, while the share of research faculty increased 52%, and the faculty to student ratio dropped nearly 10%. At the same time, engineering faculty became more diverse, as the proportion of URM tenured/tenure-track faculty increased 22%, the proportion of Black faculty increased 19%, and the proportion of female faculty increased 30%. There was little change, however, in average engineering research expenditures per FTE undergraduate across the sample.

Considering changes in degree output and faculty inputs across different institutional contexts reveals the inherent limitations of broad generalizations about both degree output and faculty inputs. Concerning degree output by institutional control, Table 4.3 shows that public institutions were primarily responsible for the growth in the numbers of engineering bachelor's degrees awarded to underrepresented minorities (20% increase), whereas private institutions saw substantial declines in degrees awarded to Black students (18% decrease) over the seven-year period. The most competitive and highly competitive institutions had greater percentage increases in URM engineering baccalaureates (26%) and the smallest reductions in Black engineering baccalaureates (2%) than institutions at other competitiveness levels. Master's institutions also increased (on a percentage change basis) URM baccalaureate output more and decreased Black baccalaureate output less than other Carnegie classes of engineering schools. And HBCUs experienced across the board declines in engineering bachelor's degrees, with a nearly 30% drop in the total number of degrees awarded to Black students from 2005 to 2011.

Table 4.2 Number of bachelor's degrees and average faculty inputs across all sample institutions.

	Total # Bachelor's Degrees			Average Faculty Inputs						
Year	All Students	URM	Black	Prop. non-TTT faculty	Prop. research faculty	Faculty-student ratio	Prop. URM faculty	Prop. Black faculty	Prop. female faculty	Engr. research exp per FTE student
2005	79425	8537	3963	0.143	0.078	0.092	0.058	0.032	0.108	14,946
2006	79418	8623	3779	0.141	0.090	0.089	0.059	0.032	0.116	15,396
2007	77909	8460	3616	0.144	0.102	0.090	0.062	0.034	0.122	15,021
2008	78397	8655	3528	0.135	0.109	0.088	0.063	0.034	0.125	15,223
2009	78929	8672	3499	0.146	0.118	0.086	0.066	0.034	0.131	14,971
2010	82828	9332	3473	0.149	0.126	0.086	0.066	0.034	0.134	15,056
2011	87578	10036	3549	0.154	0.119	0.083	0.071	0.038	0.141	14,986
7-year change	10.3%	17.6%	-10.4%	7.5%	52.1%	-9.6%	22.1%	19.0%	30.4%	0.3%

Note: Abbreviations: “Prop.” = proportion; “non-TTT” = non-tenured/tenure-track; “Engr.” = engineering; and “exp” = expenditures.

Table 4.3 Change in number of bachelor's degrees awarded and average faculty inputs from 2005 to 2011, by student race/ethnicity and institutional contexts.

	Total # Bachelor's Degrees			Average Faculty Inputs						
Institutional Contexts	All Students	URM	Black	Prop. non-TTT faculty	Prop. research faculty	Faculty-student ratio	Prop. URM faculty	Prop. Black faculty	Prop. female faculty	Engr. research exp per FTE student
All	10.3%	17.6%	-10.4%	7.5%	52.1%	-9.6%	22.1%	19.0%	30.4%	0.3%
Institutional Control										
Private	6.7%	5.7%	-17.9%	-2.6%	75.6%	-7.5%	29.0%	40.7%	34.0%	2.7%
Public	11.3%	20.4%	-8.4%	13.0%	44.8%	-11.0%	19.9%	11.3%	28.3%	0.6%
Land Grant	7.8%	7.5%	-13.2%	12.2%	57.8%	-8.4%	27.8%	32.3%	34.1%	-9.5%
Selectivity										
Highly Competitive	11.6%	25.8%	-2.0%	3.2%	60.8%	-4.8%	22.5%	29.1%	27.5%	0.6%
Very Competitive	8.3%	15.0%	-16.4%	11.3%	82.5%	-13.4%	16.3%	17.7%	31.6%	9.7%
Competitive	11.2%	13.9%	-13.3%	18.1%	19.6%	-12.5%	26.3%	17.2%	32.9%	-7.2%
Less Competitive	5.2%	8.9%	-14.2%	-18.7%	51.2%	-8.5%	14.4%	13.4%	30.5%	-5.3%
Carnegie Classification (2010)										
Doctorate/Research	10.1%	15.2%	-12.8%	15.4%	57.2%	-5.6%	13.5%	8.6%	30.8%	-0.5%
Master's	11.4%	26.2%	-2.7%	-16.8%	11.1%	-21.5%	14.2%	1.4%	32.6%	4.0%
Baccalaureate	1.4%	10.5%	-15.4%	13.0%	74.5%	-10.7%	173.1%	200.6%	23.7%	115.2%
HBCUs	-17.1%	-28.3%	-29.5%	-3.1%	167.7%	1.0%	11.8%	14.1%	51.4%	1.4%

Note: Abbreviations: "Prop." = proportion; "non-TTT" = non-tenured/tenure-track; "Engr." = engineering; and "exp" = expenditures.

Table 4.3 also illustrates heterogeneity across institutional contexts with respect to the rate of change in engineering schools' faculty inputs from 2005 to 2011. For example, although the proportion of non-tenured/tenure-track faculty increased overall (8%), it decreased in some institutional settings – at a slower rate within private institutions and HBCUs (3% decrease respectively) and at a higher rate within master's institutions (17% decrease) and less competitive and noncompetitive institutions (19% decrease). Likewise, the proportion of research faculty increased substantially on the whole – by as much as 168% at HBCUs (where the share of research faculty grew from 2% to 6%) – but increased by only 11% at master's institutions, for example. The engineering faculty-to-student ratio at HBCUs increased ever-so slightly (1%) despite overall declines, with master's colleges experiencing the greatest percentage decline (22%). Baccalaureate colleges had greater rates of increase in their shares of URM and African American tenured/tenure-track engineering faculty compared to all other institutional contexts, but rates of change in the share of female tenured/tenure-track faculty were fairly consistent across institutional contexts. Spending on engineering research increased substantially at baccalaureate institutions (115%), but decreased at land grant (10%), competitive (7%), and less/noncompetitive institutions (5%).

The information provided in Tables 4.2 and 4.3 demonstrates that engineering bachelor's degrees by student race/ethnicity and faculty inputs varied over time across all institution-year observations. Next, I decomposed this overall variation for each variable of interest into between- and within-institution components in order to confirm variation over time within institutions, a prerequisite for subsequent analyses. The results, which are presented in Table A2, indicate that all of the variables of interest did in fact change within institutions over time. Specifically, the within-institution standard deviations from the overall means of all the variables were greater than zero.

Research Question #2: Estimating an engineering degree production function

To address Research Question #2, I specified three sets of panel data models to test whether the relationships between engineering bachelor's degree output and engineering school/college inputs differed by student race/ethnicity and across institutional contexts.

Results of the Hausman Test – presented in Table A.3 – confirmed that relative to random effects, fixed effects estimation is more appropriate for estimating the basic panel data models of engineering degree production. Thus, baseline fixed effects regression models of engineering bachelor's degree production for all students, URM students and Black students were estimated to examine potential differences by student race/ethnicity in the role of faculty inputs using 20 imputed data sets. These models were estimated across 9 different strata of institutional context, including categories of institutional control (i.e., private, public, land grant), institutional selectivity (i.e., highly competitive, very competitive, competitive, less competitive), and Carnegie classification (i.e., doctorate-granting/research and master's institutions). The model of degree production for Black students was also estimated separately for HBCUs. In total, this step involved estimation of 28 separate models. The coefficient estimates obtained for these models are presented in Tables 4.4 to 4.7.

Given the functional form of the production model, which consists of a log transformed dependent variable and several log transformed independent variables, interpretation of the coefficient estimates is not exactly straightforward. (Please recall that log refers to the natural log throughout this study.) Consider the following general estimated model to understand the procedure for interpreting the coefficient estimates. A similar derivation is provided in Woolridge (2009),

$$\widehat{\log(\mathrm{y})} = \hat{\beta}_0 + \hat{\beta}_1 \log(x_1) + \hat{\beta}_2 x_2, \tag{4.1}$$

where the hat (^) above the estimates is used to denote predicted values. In microeconomic terms, the predicted coefficient $\hat{\beta}_1$ is the elasticity of y with respect to x_1, which means that when x_1 increases by 1%, y changes by $\hat{\beta}_1$%. The coefficient $\hat{\beta}_2$ is the semi-elasticity of y with respect to x_2, which is often interpreted to mean that a 1 unit change in x_2 is associated with an approximately (100*$\hat{\beta}_2$)% change in y. However, as Woolridge (2009) notes, as the change in log(y) increases, this approximation becomes less accurate. Instead, the exact percentage change in the predicted y can be calculated. Holding x_1 constant and differencing Equation 4.1 gives,

$$\Delta \widehat{\log(y)} = \hat{\beta}_2 \Delta x_2 , \tag{4.2}$$

which, upon multiplication by 100 to convert proportionate change to percentage change, reduces to,

$$\%\Delta\hat{y} = 100 * \left[\exp\left(\hat{\beta}_2 \Delta x_2\right) - 1\right]. \tag{4.3}$$

Therefore, to avoid potential approximation errors, I used Equation 4.3 to interpret all semi-elasticities (i.e., coefficient estimates of variables that were not log transformed).

In addition to the coefficient estimates, Stata's fixed effects regression output includes (among other statistics) three R^2 estimates: within, between, and overall. The within R^2 is similar to that reported with basic OLS output; it is computed using the mean deviation variables and is interpreted as the proportion of within-institution variance in the dependent variable explained by the model (Allison, 2009). (The between- and overall-R^2 have more complex interpretations, which are not critical to the focus of my study.) Unfortunately, Stata does not automatically calculate R^2 when imputed data are used. However, according to Rubin's (1987) rules for multiple imputation, the estimate of the value of interest such as R^2 should be computed for each imputation, and the overall value will be the mean of these estimates. Therefore, with the help of the Stata command `mi xeq`, I "manually" obtained the within-R^2 for each of 20 imputed data sets and computed the mean R^2 for all the models.

Variations in faculty effects by student race/ethnicity. The baseline fixed effects estimates for the full sample of institutions, which are presented in Table 4.4, clearly suggest variation in the relationships between faculty inputs and degree output by student race/ethnicity. Referring first to the estimates obtained for the model of bachelor's degrees to all students (second column of Table 4.4), the share of research faculty was negatively related, while the faculty-to-student ratio was positively related, to the number of degrees awarded to all students, controlling for other faculty and student characteristics. More precisely, for every percentage point increase in the share of research faculty, the number of degrees awarded to all students is predicted to decrease 19% (from Equation 4.3, 100*[exp[-0.21] – 1] = 19%), controlling for other faculty and student characteristics. Increasing the faculty-to-student ratio by 1 is associated with an 88% increase in the number of degrees awarded, controlling for other variables. The “enrollment effect” is also statistically significant and positive; a 1% increase in FTE undergraduate enrollment is associated with a .35% increase in bachelor’s degrees. Interestingly, a 1% increase in full-time doctoral enrollment is associated with a .07% increase in bachelor’s degrees. The R^2 of .182 suggests that, on average, the model explained 18% of the variation within institutions in log(degrees) awarded to all students over the period 2005 to 2011.

In contrast, estimates for the model of engineering bachelor’s degrees to underrepresented minority students indicate that no faculty inputs are significantly related to the number of degrees awarded to URMs when all institutions are pooled together (third column of Table 4.4). There are statistically significant enrollment effects: a 1% increase in URM FTE enrollment is associated with a .75% increase in degrees to URMs; and a 1-percentage point increase in the share of URM undergraduates is associated with a 97% decrease in degrees awarded to URMs, controlling for other factors. And a 1-percentage point increase in the share of women among bachelor’s degree recipients is associated with a 136% increase in the number of bachelor’s degrees awarded to URMs. This model explained nearly 14% of the variation within institutions in log(degrees) awarded to URM students over the sample period.

The estimates obtained for the model of engineering bachelor's degrees to Black students across the pooled sample of institutions differ from the URM student estimates. Whereas no faculty inputs were significant predictors of URM degrees, a 1-percentage point increase in the share of female tenured/tenure-track engineering faculty was associated with an 82% decrease in the number of degrees awarded to Black students, controlling for faculty and student characteristics. Also noteworthy, no student characteristics were found to be statistically significant predictors of the number of degrees awarded to Black students. This model had noticeably less explanatory power compared to the models for all and URM students. The R^2 of .023 suggests it explains only 2% of the variation within institutions in log(degrees) awarded to Black students.

Table 4.4 Fixed effects estimates of log engineering bachelor's degrees by student race/ethnicity using full sample (all institutions) and 20 imputed data sets.

Variables	All students	URMs	Blacks
Faculty Inputs			
Proportion non-TTT faculty	-0.06	-0.09	-0.14
	(0.10)	(0.17)	(0.21)
Proportion research faculty	-0.21**	0.18	-0.39
	(0.08)	(0.19)	(0.23)
Faculty-student ratio	0.63*	0.87	1.04
	(0.28)	(0.52)	(0.77)
Proportion URM faculty	0.04	0.08	0.48
	(0.19)	(0.37)	(0.57)
Proportion female faculty	-0.40	-0.12	-1.71*
	(0.29)	(0.54)	(0.85)
Log engr research exp per FTE	0.02	0.04	-0.06
	(0.02)	(0.05)	(0.07)
Student Characteristics			
Log URM FTE	0.06	0.75***	0.29
	(0.06)	(0.21)	(0.19)
Log total FTE	0.35***	-0.27	0.02
	(0.09)	(0.26)	(0.26)
Proportion URM PhD	0.05	0.36	0.50
	(0.20)	(0.36)	(0.52)
Log total PhD	0.07***	0.03	-0.02
	(0.01)	(0.05)	(0.07)
Proportion female B.S.	0.27	0.86*	0.51
	(0.17)	(0.40)	(0.52)
Proportion URM FTE	-0.85	-3.55**	-1.98
	(0.57)	(1.14)	(1.27)
R^2, within	.182	.137	.023
Observations	1206	1200	1132
Institutions	182	182	182

Notes: Standard errors in parentheses
legend: * p<0.05; ** p<0.01; *** p<0.001

Despite these interesting, perhaps curious, initial findings, it is my contention that they hold limited substantive meaning. As discussed in Chapter 3, the fixed effects estimator (i.e., *within* estimator) works by estimating coefficients based on variation within each institution over time, then averaging those results across the sample.

Therefore, given the broad assortment of institutions in the pooled sample, the truly meaningful relationships might be distorted. More valuable insights about engineering degree production might arise from consideration of institutional context in examining variations in faculty effects across student race/ethnicity.

Variations in faculty effects by student race/ethnicity and institutional context. The baseline fixed effects regression models were next estimated across multiple institutional contexts. These results are presented in this section by student race/ethnicity category.

All students. Table 4.5 presents the fixed effects estimates of log engineering degrees awarded to all students by institutional control, selectivity, and Carnegie classification. The results suggest differential estimated effects of faculty inputs on bachelor's degree output for all students by institutional context. In particular, the proportion of research faculty was negatively related to engineering bachelor's degree output to all students only within public institutions, very competitive institutions, and doctorate-granting/research institutions. For these institution types, a 1-percentage point increase in the share of research faculty was associated with a 16% to 31% decrease in the number of engineering bachelor's degrees conferred to all students, controlling for other faculty and student characteristics. A 1-unit increase in engineering faculty-to-student ratio was predictive of a 23% to 166% increase in engineering bachelor's degree output for all students within private institutions, highly competitive and very competitive institutions, and doctorate-granting/research institutions, controlling for other variables.

No other[6] faculty inputs were significantly related to the number of engineering bachelor's degrees conferred to all students.

Table 4.5 also shows that a statistically significant enrollment effect was detected for the all-students engineering degree production models. Specifically, within public and land grant institutions, highly and very competitive institutions, and doctorate-granting/research institutions, a 1% increase in total FTE undergraduate engineering enrollment was associated with a .34% to .51% increase in the number of bachelor's degrees conferred. Other student (control) variables were statistically predictive of engineering bachelor's degree output for all students. Engineering doctoral enrollment was positively related to bachelor's degree output within all institution types except land grant, very competitive, and master's institutions. The proportion of URM FTE undergraduates in private and competitive institutions and the proportion of URM doctoral students in highly competitive institutions were negatively related to the numbers of engineering bachelor's degrees awarded to all students.

The within-R^2's estimated for the all-students degree production models also varied across institutional contexts. Table 4.5 indicates that these models explained 16% to 31% of the variance within institutions in the numbers of degrees awarded to all students.

[6] The negative relationship between engineering research expenditures per FTE and degree output for all students was statistically significant. However, because this relationship was not detected in any other models, it could likely be a consequence of chance given the large number of hypotheses (models) tested.

Table 4.5 Fixed effects estimates of log engineering bachelor's degrees to ALL STUDENTS by institutional control, institutional selectivity, and Carnegie classification using 20 imputed data sets.

		Institutional Control			Selectivity				Carnegie 2010	
Variables	All Inst.	Private	Public	Land Grant	Highly Competitive	Very Competitive	Competitive	Less Competitive	Doctoral/ Research	Master's
Faculty Inputs										
Proportion non-TTT faculty	-0.06	-0.19	0.12	-0.11	-0.33	0.07	0.09	0.23	-0.09	-0.02
	(0.10)	(0.19)	(0.10)	(0.21)	(0.23)	(0.16)	(0.13)	(0.29)	(0.12)	(0.37)
Proportion research faculty	-0.21**	-0.26	-0.17*	-0.29	-0.15	-0.37**	-0.05	-0.08	-0.20*	-0.31
	(0.08)	(0.17)	(0.07)	(0.18)	(0.14)	(0.12)	(0.13)	(0.29)	(0.08)	(0.27)
Faculty-student ratio	0.63*	0.88*	0.23	1.81	0.98*	0.21	-0.40	-0.56	0.67*	3.28
	(0.28)	(0.42)	(0.33)	(1.40)	(0.45)	(0.45)	(0.78)	(1.56)	(0.28)	(2.49)
Proportion URM faculty	0.04	0.30	-0.21	0.87	-0.39	-0.26	-0.07	0.45	-0.25	0.26
	(0.19)	(0.23)	(0.34)	(0.56)	(0.47)	(0.61)	(0.23)	(0.48)	(0.30)	(0.32)
Proportion female faculty	-0.40	-0.67	-0.15	-0.35	-1.20	-0.22	-0.17	-0.13	-0.61	1.19
	(0.29)	(0.56)	(0.29)	(0.37)	(0.72)	(0.45)	(0.41)	(0.24)	(0.34)	(1.01)
Log eng. research expenditures per FTE	0.02	0.03	0.01	0.07	0.03	-0.01	0.01	0.06	0.04	-0.10*
	(0.02)	(0.06)	(0.03)	(0.05)	(0.05)	(0.03)	(0.04)	(0.05)	(0.03)	(0.04)
Student Characteristics										
Log URM FTE	0.06	0.21	0.00	-0.01	0.10	-0.03	0.22	-0.02	0.07	-0.11
	(0.06)	(0.11)	(0.05)	(0.09)	(0.13)	(0.07)	(0.12)	(0.08)	(0.06)	(0.34)
Log total FTE	0.35***	0.28	0.34***	0.51**	0.40**	0.37**	0.08	0.10	0.37***	0.51
	(0.09)	(0.17)	(0.09)	(0.18)	(0.14)	(0.11)	(0.19)	(0.29)	(0.09)	(0.48)

Table 4.5 (Cont.) Fixed effects estimates of log engineering bachelor's degrees to ALL STUDENTS by institutional control, institutional selectivity, and Carnegie classification using 20 imputed data sets.

		Institutional Control			Selectivity				Carnegie 2010	
Variables	All Inst.	Private	Public	Land Grant	Highly Comp-etitive	Very Comp-etitive	Comp-etitive	Less Comp-etitive	Doctoral/ Research	Master's
Proportion URM Ph.D.	0.05	-0.24	0.14	0.45	-1.01**	-0.58	0.36	0.21	0.17	-0.09
	(0.20)	(0.48)	(0.19)	(0.25)	(0.37)	(0.35)	(0.28)	(0.28)	(0.23)	(0.46)
Log total Ph.D.	0.07***	0.13**	0.06***	0.08	0.14**	0.05	0.07**	0.06*	0.06***	0.09
	(0.01)	(0.04)	(0.02)	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.05)
Proportion female B.S.	0.27	0.20	0.32	0.29	0.37	-0.22	0.40	0.33	0.27	0.81
	(0.17)	(0.33)	(0.22)	(0.37)	(0.33)	(0.44)	(0.27)	(0.36)	(0.19)	(0.40)
Proportion URM FTE	-0.85	-2.21*	-0.14	-0.20	-1.06	0.06	-1.56*	0.14	-1.02	0.59
	(0.57)	(0.97)	(0.39)	(1.29)	(1.06)	(0.50)	(0.73)	(0.78)	(0.74)	(1.11)
R^2, within	.182	.296	.162	.212	.312	.212	.183	.208	.192	.211
Observations	1206	319	887	359	425	336	356	89	1107	78
Institutions	182	49	133	52	63	51	54	14	164	15

Notes: Standard errors in parentheses
legend: * p<0.05; ** p<0.01; *** p<0.001
This set of analyses includes comparisons across 9 institutional contexts, which increases the probability of Type I errors.

URM students. Table 4.6 shows that the estimated effects of faculty inputs on engineering bachelor's degree outputs for underrepresented minority students also vary across institutional contexts. A 1-unit increase in the share of engineering research faculty was associated with a 41% decrease in the number of bachelor's degrees conferred to URM students within private institutions and a 58% increase in degrees to URMs in public institutions, controlling for other faculty and student variables. Within private institutions, highly competitive institutions, and research institutions, a unit increase in engineering faculty-to-student ratio was predictive of 180% to 447% increase (i.e., roughly a 2- to 4-fold increase) in the number of bachelor's degrees to URM students. And, contrary to the all-students production models, faculty demographic variables were significantly related to degree output for URM students within less competitive institutions. In particular, a 1-percentage point increase in the proportion of URM tenured/tenure-track engineering faculty was associated with a nearly 13-fold (1274%) increase in the number of bachelor's degrees to URMs. But a 1-percentage point increase in the proportion of female tenured/tenure-track engineering faculty was associated with a 79% decrease in bachelor's degrees to URMs.

Similar to the all-students degree production models, enrollment effects were statistically significant for URMs within multiple institutional contexts. Specifically, a 1% increase in URM FTE undergraduate enrollment was associated with a .62% to .94% increase in the number of degrees awarded to URMs within all institutions except highly competitive and master's institutions. The estimates indicate that three other control variables were statistically related to degree output for URMs in some institutional settings. Doctoral enrollment within private and highly competitive institutions and the share of female baccalaureate recipients within public, highly competitive, and research institutions were positively related to bachelor's degree production for URMs. The proportion of URM undergraduates was negatively related to degree production for URMS within private and public institutions, competitive institutions, and research institutions.

Finally, compared to the all-students degree production models, the within-R^2 estimates indicate that the URM-students models have somewhat less explanatory power. The proportion of within-institution variance explained by these models ranged from 11% to 28% across institutional contexts.

Table 4.6 Fixed effects estimates of log engineering bachelor's degrees to URM STUDENTS by institutional control, institutional selectivity, and Carnegie classification using 20 imputed data sets.

		Institutional Control			Selectivity				Carnegie 2010	
Variables	All Inst.	Private	Public	Land Grant	Highly Comp-etitive	Very Comp-etitive	Comp-etitive	Less Comp-etitive	Doctoral/ Research	Master's
Faculty Inputs										
Proportion non-TTT faculty	-0.09	-0.19	0.11	-0.94	-0.26	0.41	-0.05	0.68	-0.28	-0.60
	(0.17)	(0.17)	(0.24)	(0.74)	(0.23)	(0.37)	(0.35)	(0.67)	(0.18)	(1.04)
Proportion research faculty	0.18	-0.53*	0.46*	0.07	-0.03	0.13	0.79	0.11	0.13	-0.14
	(0.19)	(0.25)	(0.22)	(0.59)	(0.22)	(0.39)	(0.43)	(0.60)	(0.20)	(0.59)
Faculty- student ratio	0.87	1.70**	0.19	4.92	1.42*	-0.78	0.23	-4.14	1.03*	9.08
	(0.52)	(0.59)	(0.74)	(4.31)	(0.58)	(0.74)	(1.52)	(5.57)	(0.49)	(6.46)
Proportion URM faculty	0.08	0.22	-0.42	1.74	0.09	-2.41	-0.18	2.62*	-0.60	1.37
	(0.37)	(0.39)	(0.86)	(1.46)	(0.57)	(1.44)	(0.60)	(1.20)	(0.66)	(1.09)
Proportion female faculty	-0.12	0.33	-0.11	-0.77	-0.28	-0.25	0.58	-1.58*	-0.35	2.22
	(0.54)	(0.84)	(0.67)	(1.09)	(1.00)	(1.27)	(0.94)	(0.69)	(0.59)	(2.64)
Log eng. research expenditures per FTE	0.04	-0.07	0.11	0.26	0.01	-0.04	0.09	0.11	0.05	-0.10
	(0.05)	(0.08)	(0.06)	(0.16)	(0.07)	(0.11)	(0.10)	(0.23)	(0.06)	(0.10)
Student Characteristics										
Log URM FTE	0.75***	0.71**	0.76**	0.79**	0.48	0.83*	0.62*	0.94***	0.74**	0.16
	(0.21)	(0.21)	(0.25)	(0.29)	(0.30)	(0.33)	(0.28)	(0.17)	(0.22)	(0.66)
Log total FTE	-0.27	-0.16	-0.30	0.14	0.08	-0.53	-0.21	-0.78	-0.25	1.34
	(0.26)	(0.36)	(0.29)	(0.40)	(0.38)	(0.38)	(0.30)	(0.57)	(0.27)	(1.21)

Table 4.6 (Cont.) Fixed effects estimates of log engineering bachelor's degrees to URM STUDENTS by institutional control, institutional selectivity, and Carnegie classification using 20 imputed data sets.

		Institutional Control			Selectivity				Carnegie 2010	
Variables	All Inst.	Private	Public	Land Grant	Highly Comp-etitive	Very Comp-etitive	Comp-etitive	Less Comp-etitive	Doctoral/ Research	Master's
Proportion URM Ph.D.	0.36	0.47	0.09	-0.48	0.03	0.24	0.24	0.59	0.65	0.39
	(0.36)	(0.87)	(0.38)	(0.60)	(1.00)	(1.12)	(0.50)	(0.40)	(0.41)	(0.87)
Log total Ph.D.	0.03	0.20*	-0.02	-0.04	0.22*	-0.02	0.01	-0.08	0.01	0.09
	(0.05)	(0.08)	(0.06)	(0.13)	(0.09)	(0.10)	(0.07)	(0.17)	(0.06)	(0.12)
Proportion Female B.S.	0.86*	0.41	1.39**	2.18	1.26*	0.16	1.20	0.30	1.03*	0.73
	(0.40)	(0.63)	(0.52)	(1.20)	(0.58)	(0.85)	(0.81)	(0.97)	(0.41)	(1.43)
Proportion URM FTE	-3.55**	-4.87**	-2.54*	-1.70	-2.87	-2.83	-3.71*	-1.19	-3.17*	-2.11
	(1.14)	(1.72)	(1.27)	(2.20)	(2.84)	(2.08)	(1.46)	(1.25)	(1.49)	(2.16)
R^2, within	.137	.173	.159	.266	.171	.192	.113	.346	.140	.275
Observations	1200	319	881	354	425	334	354	87	1101	78
Institutions	182	49	133	52	63	51	54	14	164	15

Notes: Standard errors in parentheses
legend: * p<0.05; ** p<0.01; *** p<0.001
This set of analyses includes comparisons across 9 institutional contexts, which increases the probability of Type I errors.

Black students. Table 4.7 presents the fixed effects coefficient estimates for the engineering bachelor's degree production model for Black students. These results indicate that similar to the all-students and URM-students production models, the share of research faculty and faculty-to-student ratio were statistically related to degree output for Black students within some institutional contexts. Specifically, a 1-percentage point increase in the share of engineering research faculty was associated with a 40% decrease in bachelor's degrees to Black students in doctorate-granting/research institutions and 83% decrease in the number of degrees conferred to Black students at HBCUs, controlling for other variables. On the other hand, within private and highly competitive institutions, a unit increase in the engineering faculty-to-student ratio was associated with 5- to 6-fold (505% to 590%) increase in bachelor's degree output for Black students, controlling for other variables. Similar to the estimates from the models for URM students, faculty demographic characteristics were predictive of degree output for Black students. Within land grant and less competitive institutions, a unit increase in the share of URM tenured and tenure-track engineering faculty was associated with a 46- to 170-fold (4550% to 17,400%) increase in degree output to Black students. And within highly competitive and doctorate institutions, the share of female tenured and tenure-track engineering faculty was associated with a 97% and 89% decrease in degree output to Black students respectively. The estimates also indicate that unlike the models for all students and URM students, a unit increase in the share of non-tenured/tenure-track engineering teaching faculty was associated with a 50% decline in engineering bachelor's degrees conferred to Black students.

Also similar to the degree production model estimates for all students and URM students, enrollment effects were statistically significant but only in private and highly competitive institutions. In these settings, a 1% increase in URM undergraduate enrollment was predictive of a .77% to .85% increase in the number of engineering bachelor's degrees to Black students. Unlike the models for all students and URM students, doctoral enrollment was negatively related to bachelor's degree output for Black students but only within less competitive institutions. The proportion of URM engineering doctoral students in highly competitive institutions and the proportion of URM engineering undergraduates in private institutions were negatively related to bachelor's degree output for Black students.

Compared to the engineering degree production models for all students and URM students, the models for Black students have a much broader range of explanatory power. The within-R^2 estimates indicate that the models for Black students explain as little as 1% of the variation in degree output within public institutions and as much as 61% of variation in degree output within HBCUs. Because the R^2 gives an indication of how well the independent variables predict the outcome, this variation in R^2 suggests that the true engineering degree production model for Black students involves different inputs across different institutional settings, and in the case of low R^2 important inputs remain unobserved.

Table 4.7 Fixed effects estimates of log engineering bachelor's degrees to BLACK STUDENTS by institutional control, institutional selectivity, and Carnegie classification using 20 imputed data sets.

		Institutional Control			Selectivity				Carnegie 2010		
Variables	All Inst.	Private	Public	Land Grant	Highly Comp-etitive	Very Comp-etitive	Comp-etitive	Less Comp-etitive	Ph.D.	M.A./ M.S.	HBCU
Faculty Inputs											
Proportion non-TTT faculty	-0.14	-0.24	0.11	-0.61	-0.702*	0.26	0.18	0.96	-0.35	0.26	-0.29
	(0.21)	(0.28)	(0.27)	(0.68)	(0.30)	(0.44)	(0.33)	(1.23)	(0.23)	(0.84)	(0.41)
Proportion research faculty	-0.39	-0.42	-0.33	-0.66	-0.37	-0.73	0.01	-0.76	-0.51*	1.38	-1.79*
	(0.23)	(0.37)	(0.26)	(0.68)	(0.27)	(0.44)	(0.42)	(0.75)	(0.23)	(0.96)	(0.65)
Faculty-student ratio	1.04	1.80*	0.19	2.42	1.93**	-0.20	-0.85	-5.83	1.39	-4.25	1.38
	(0.77)	(0.86)	(0.72)	(4.00)	(0.70)	(0.98)	(1.57)	(8.94)	(0.72)	(6.40)	(2.64)
Proportion URM faculty	0.48	1.11	0.11	3.84*	-0.43	-2.93	-0.76	5.17***	-0.55	-0.02	1.07
	(0.57)	(0.63)	(1.12)	(1.64)	(0.86)	(2.23)	(0.70)	(0.95)	(0.86)	(2.17)	(1.37)
Proportion female faculty	-1.71*	-2.37	-0.84	-1.62	-3.44*	-2.53	1.41	-4.32	-2.21*	-0.65	-1.79
	(0.85)	(1.45)	(1.04)	(2.23)	(1.45)	(1.65)	(1.22)	(2.67)	(0.91)	(2.95)	(2.55)
Log eng. research expenditures per FTE	-0.06	-0.23	0.02	0.23	-0.05	-0.13	-0.10	0.17	-0.09	-0.05	0.77
	(0.07)	(0.13)	(0.07)	(0.20)	(0.10)	(0.17)	(0.11)	(0.34)	(0.08)	(0.24)	(0.34)
Student Characteristics											
Log URM FTE	0.29	0.85**	-0.06	-0.48	0.77*	-0.04	0.45	0.64	0.26	-0.11	1.75
	(0.19)	(0.28)	(0.19)	(0.28)	(0.38)	(0.20)	(0.48)	(0.84)	(0.22)	(0.97)	(2.58)
Log total FTE	0.02	-0.43	0.27	0.95	-0.04	0.16	-0.78	-0.49	0.06	0.82	-0.17
	(0.26)	(0.46)	(0.24)	(0.52)	(0.46)	(0.30)	(0.61)	(1.34)	(0.26)	(1.61)	(2.73)

Table 4.7 (Cont.) Fixed effects estimates of log engineering bachelor's degrees to BLACK STUDENTS by institutional control, institutional selectivity, and Carnegie classification using 20 imputed data sets.

		Institutional Control			Selectivity				Carnegie 2010		
Variables	All Inst.	Private	Public	Land Grant	Highly Comp-etitive	Very Comp-etitive	Comp-etitive	Less Comp-etitive	Ph.D.	M.A./ M.S.	HBCU
Proportion URM Ph.D.	0.50	-0.39	0.63	0.60	-2.43*	0.14	0.52	0.60	0.92	-0.33	0.56
	(0.52)	(0.95)	(0.55)	(0.82)	(1.06)	(1.16)	(0.64)	(0.50)	(0.52)	(1.13)	(0.47)
Log total Ph.D.	-0.02	0.13	-0.05	-0.06	-0.01	-0.07	0.18	-0.46**	-0.05	0.16	0.09
	(0.07)	(0.11)	(0.07)	(0.17)	(0.11)	(0.09)	(0.10)	(0.15)	(0.07)	(0.25)	(0.10)
Proportion female B.S.	0.51	0.57	0.46	-1.29	1.35	-0.74	0.14	0.92	0.55	2.87	-0.44
	(0.52)	(0.88)	(0.60)	(1.36)	(0.77)	(1.50)	(0.75)	(2.27)	(0.51)	(2.73)	(1.10)
Proportion URM FTE	-1.98	-5.29*	0.16	4.38	-5.24	-1.12	-2.95	0.78	-1.32	-3.44	-5.10
	(1.27)	(1.99)	(1.25)	(2.24)	(3.94)	(2.08)	(1.83)	(6.51)	(1.78)	(2.78)	(4.45)
R^2, within	.023	.119	.011	.059	.113	.062	.040	.335	.034	.140	.607
Observations	1132	308	824	314	421	301	337	73	1040	74	48
Institutions	182	49	133	52	63	51	54	14	164	15	7

Notes: Standard errors in parentheses
legend: * p<0.05; ** p<0.01; *** p<0.001
This set of analyses includes comparisons across 10 institutional contexts, which increases the probability of Type I errors.

Alternative inputs models. Models using alternative inputs were estimated to test whether selected measures of capital and institutional inputs were predictive of engineering degree output by student race ethnicity. Given their focus on measures of institutional finance, these models were estimated by institutional control but not across other institutional contexts. I made this decision based on research reviewed in Chapter 2, which emphasized that most variation across institutions in financial accounting and reporting arises between public and private institutions (Toutkoushian, 2001).

I used an incremental approach to investigate the potential relationship between each capital input measure and engineering degree output separately, for each of the race/ethnicity-focused outcomes. The results indicate that variations in neither engineering equipment expenditures nor institutional endowment/gift/contract revenue per FTE were statistically related to engineering degree output. This was the case in fixed effects models by institutional control without faculty inputs (Table 4.8) and with faculty inputs (Table 4.9). Not only were these measures statistically insignificant across the board, but the coefficient estimates of the capital variables were also approximately equal to zero in all cases.

Table 4.8 Fixed effects estimates of log engineering bachelor's degrees by student race/ethnicity and institutional control, using capital inputs and 20 imputed data sets.

	All Students		URM Students		Black Students	
Variables	Private	Public	Private	Public	Private	Public
Log exp for equip per FTE	0.03	0.01	0.00	0.01	-0.04	-0.05
	(0.02)	(0.01)	(0.05)	(0.02)	(0.06)	(0.03)
Log endow, etc. revenue per FTE	0.00	-0.01	-0.03	0.01	-0.01	0.01
	(0.02)	(0.01)	(0.03)	(0.02)	(0.05)	(0.03)
Faculty Inputs	No	No	No	No	No	No
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2, within	0.239	0.078	0.139	0.107	0.073	0.019
Observations	226	690	226	684	218	640
Institutions	48	132	48	132	48	132

Notes: Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Table 4.9 Fixed effects estimates of log engineering bachelor's degrees by student race/ethnicity and institutional control, using capital and faculty inputs and 20 imputed data sets.

	All Students		URM Students		Black Students	
Variables	Private	Public	Private	Public	Private	Public
Capital Inputs						
Log exp for equip per FTE	0.03	0.01	0.03	-0.01	0.05	-0.05
	(0.02)	(0.01)	(0.06)	(0.02)	(0.06)	(0.03)
Log endow, etc. revenue per FTE	-0.01	0.00	-0.04	0.01	-0.05	0.03
	(0.02)	(0.01)	(0.04)	(0.02)	(0.05)	(0.03)
Faculty Inputs	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2, within	0.346	0.106	0.228	0.138	0.208	0.032
Observations	214	672	214	666	206	623
Institutions	47	130	47	130	47	130

Notes: Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

The second set of alternative inputs models were intended to examine the potential relationships between broad institutional expenditures by category and engineering degree output. However, multiple imputation of all the missing categorical expenditure variables was not possible due to their extensive missingness. Instead, I estimated the effects of changes in total education and related expenditures per FTE on engineering degree output. These models also included institution-wide student characteristics (control variables): Pell grant dollars per FTE and mean SAT math scores. The estimates for these models, which are presented in Table 4.10, indicate that variations in institutions' educational and general expenditures over the sample period were statistically unrelated to engineering bachelor's degree output. Variations in the mean SAT math scores of the entire institution were also unrelated to engineering bachelor's degree output; and the magnitude of the estimated effect was nearly zero in all cases. Changes in the amount of Pell grant dollars dispersed were statistically unrelated to the number of bachelor's degrees awarded to all students and URM students at public and private institutions and unrelated to the number of degrees awarded to Black students at public institutions. However, a 1% increase in Pell grant dollars at private institutions was associated with a .22% decrease in the number of engineering bachelor's degrees awarded to Black students.

Table 4.10 Fixed effects estimates of log engineering bachelor's degrees by student race/ethnicity and institutional control, using broad institutional inputs, faculty inputs, and 20 imputed data sets.

	All Students		URM Students		Black Students	
Variables	Private	Public	Private	Public	Private	Public
Broad Institutional Inputs						
Log E&G†	-0.18	-0.08	-0.25	-0.13	-0.52	-0.28
exp per FTE	(0.10)	(0.07)	(0.20)	(0.16)	(0.34)	(0.21)
Log Pell grant	-0.03	0.03	-0.07	0.11	-0.22*	-0.07
dollars per FTE	(0.06)	(0.03)	(0.07)	(0.07)	(0.11)	(0.11)
Mean SAT math	0.00	0.00	0.00	0.00	0.00	0.00
score	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Faculty Inputs	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2, within	0.387	0.105	0.070	0.075	0.163	0.032
Observations	260	739	260	733	252	687
Institutions	47	130	47	130	47	130

Notes: Standard errors in parentheses
†Total education and general expenditures
* p<0.05; ** p<0.01; *** p<0.001

It is worth noting that although the estimates for the faculty inputs are not shown above in Tables 4.9 and 4.10, all of the alternative inputs models that included faculty variables yielded coefficient estimates similar to those predicted in the baseline models for public and private institutions (Tables 4.5, 4.6, and 4.7).

Dynamic panel model of engineering degree production. The final step of addressing Research Question #2 involved estimating a dynamic model of engineering degree production in order to relax the exogeneity assumption of basic fixed effects regression. Unfortunately, Stata 12.1 does not support dynamic panel model estimation using multiply imputed data, so this set of analyses is based on unimputed data. However, before proceeding with the analysis, I reconsidered the extent of missingness on the variables of interest and made a few adjustments to the baseline model specification. Specifically, given that the doctoral enrollment variables were missing on as much as 40% of the observations, I dropped these variables from the set of student control variables. Comparing the estimates obtained using imputed and unimputed data helped to confirm this approach. That is, the estimates based on imputed and unimputed data for the baseline model that included doctoral enrollment variables were inconsistent. Yet, the estimates based on imputed data that included doctoral variables were consistent with the estimates based on unimputed data that did not include doctoral variables. Because the main goal of this dynamic analysis was simply to explore the consequences of relaxing the exogeneity assumption, estimates were only obtained by institutional control and other institutional contexts were not examined.

The procedures for estimating the dynamic model using the Arellano-Bond estimator (via the `xtabond` Stata command) which were outlined in Chapter 3, indicated my intent to estimate a models that included one lag of the dependent variables (i.e., log bachelor's degrees by race/ethnicity at time, t-1). If this specification – with one lag of the dependent variable, log engineering degrees – was appropriate for my data, then the assumption of no serial correlation in the random error would not be violated. Therefore, after estimating each dynamic model, I evaluated the result of the Arellano-Bond test for serial correlation. The results of this specification test for the dynamic models of bachelor's degrees by race/ethnicity and institutional control are presented in Table 4.11.

Table 4.11 Arellano-Bond tests for serial correlation for dynamic models of log engineering bachelor's degrees by race/ethnicity and institutional control.

		Private Institutions		Public Institutions	
	Order	z	Prob > z	z	Prob > z
All	1	-3.14	0.00	-3.12	0.00
Students	2	1.00	0.32	1.37	0.17
	3	-	-	-	-
URM	1	-2.73	0.01	-5.03	0.00
Students	2	-0.99	0.32	-2.29	0.02
	3	-	-	1.26	0.20
Black	1	-3.37	0.00	-4.51	0.00
Students	2	-0.80	0.43	-1.44	0.15
	3	-	-	-	-

Note: H0: no serial correlation

Referring to Table 4.11, the null hypothesis of no serial correlation (mathematiclly, $\mathrm{Cov}\left(\Delta\varepsilon_{it}, \Delta\varepsilon_{i,t-k}\right) = 0 \; for \; k = 1, 2, 3$) is rejected at a significance level of α = 0.05 if Prob < 0.05 (Cameron & Trivedi, 2010). As noted, serial correlation is expected at order = 1 but not at higher orders. Therefore, if Prob < 0.05 when order = 2 or 3, then the errors are serially correlated and the coefficient estimates are inconsistent. The results in provided in Table 4.11 indicate that, of the 12 dynamic models specified, serial correlation of the error terms was detected in only one model. Specifically, there is evidence of serial correlation in the model estimating log engineering bachelor’s degrees to URM students at public institutions because Prob > 0.02 at order 2. This result indicated that a second lag of the dependent variable was warranted for this model. The results of the specification test after adding log engineering degrees to URMs at time, t-2 as a predictor, which are provided in Table 4.12, showed no evidence of serial correlation.

Table 4.12 Arellano-Bond tests for serial correlation for dynamic models of log engineering bachelor's degrees to URMs, including 2 lags of the dependent variable.

		Public Institutions	
	Order	z	Prob > z
URM	1	-2.87	0.00
Students	2	-1.31	0.19
	3	0.52	0.60

Note: H0: no serial correlation

The coefficient estimates for the dynamic degree production models are presented in Table 4.13. When controlling for the number of degrees awarded to all students in the previous year, all faculty inputs were statistically insignificant within both private and public institutions. However, faculty-to-student ratio was predictive of degrees awarded to URM and Black students at private institutions, even after controlling for degrees awarded in the previous year. In fact, a unit increase in the engineering faculty-to-student ratio was associated with a 7.5-fold increase in bachelor's degrees to URMs and a more than 14-fold increase in degrees to Black students at private institutions. With respect to public institutions, a 1% increase in engineering research expenditures was associated with a .08% increase in the number of engineering degrees awarded to Black students, controlling for the number of degrees awarded in the previous year. A unit increase in the engineering faculty-to-student ratio was associated with a 64% decrease in the number of degrees awarded to URMs. This estimate is clearly suspect, since we would more likely expect the faculty-to-student ratio to be positively related to degree output based on prior findings. This unexpected result might be attributable to violation of the serial correlation assumption, which was indicated in Table 4.11.

In general, the statistical significance of the estimates from the dynamic models differ somewhat from the basic fixed effects models presented in Tables 4.5, 4.6, and 4.7. However, it is difficult to draw any conclusions about these differences since the fixed effects models used imputed data and controlled for doctoral student enrollment and the dynamic models did not. At a minimum, the preliminary dynamic model estimates confirm the importance of engineering faculty-to-student ratio for bachelor's degree output at private institutions and suggest the need for further consideration of dynamic specifications of the production function.

Table 4.13 Dynamic estimates of log engineering degrees by race/ethnicity and institutional control using unimputed data.

	All Students		URM Students		Black Students	
	Private	Public	Private	Public	Private	Public
Lagged Dependent Variables†						
L1. (log total B.S.)	0.19	0.19				
	(0.13)	(0.17)				
L1. (log URM B.S.)			-0.11	0.10		
			(0.11)	(0.17)		
L2. (log URM B.S.)				-0.06		
				(0.08)		
L3. (log AfAm B.S.)					0.19	0.09
					(0.14)	(0.11)
Faculty Inputs						
Proportion non-TTT faculty	-0.02	-0.11	-0.11	-0.16	-0.57	-0.30
	(0.17)	(0.10)	(0.32)	(0.20)	(0.45)	(0.32)
Proportion research faculty	-0.05	-0.10	-0.34	0.20	-0.89	-0.51
	(0.21)	(0.09)	(0.40)	(0.23)	(0.71)	(0.35)
Faculty-student ratio	0.43	0.13	2.14*	-1.01*	4.97**	-0.63
	(0.45)	(0.25)	(1.07)	(0.44)	(1.52)	(0.66)
Proportion URM faculty	-0.08	-0.09	0.09	0.34	-0.28	0.52
	(0.17)	(0.33)	(0.50)	(0.76)	(1.12)	(1.00)

Table 4.13 (Cont.) Dynamic estimates of log engineering degrees by race/ethnicity and institutional control using unimputed data.

	All Students		URM Students		Black Students	
Variables	Private	Public	Private	Public	Private	Public
Proportion female faculty	0.16	-0.08	1.05	-0.20	1.29	-1.38
	(0.30)	(0.29)	(0.97)	(0.73)	(1.64)	(0.93)
Log eng. research expenditures per FTE	0.01	0.02	0.09	0.06	0.04	0.08*
	(0.02)	(0.02)	(0.06)	(0.03)	(0.12)	(0.04)
Student Characteristics						
Log URM FTE	0.27*	-0.08*	0.31	0.69	-0.05	-0.50
	(0.11)	(0.04)	(0.30)	(0.36)	(0.35)	(0.49)
Log total FTE	-0.02	0.48***	0.24	-0.11	0.39	0.94
	(0.17)	(0.09)	(0.64)	(0.45)	(0.73)	(0.61)
Proportion female B.S.	-0.16	0.23	-0.16	1.30*	-1.03	1.37*
	(0.16)	(0.23)	(0.57)	(0.58)	(0.97)	(0.67)
Proportion URM FTE	-2.41*	1.08***	-2.94	-2.19	-5.65*	1.89
	(0.94)	(0.32)	(2.00)	(1.89)	(2.34)	(2.07)
Observations	316	722	312	567	275	619
Institutions	69	163	68	161	63	150

Notes: Standard errors in parentheses
† L1 refers to lag at time, t-1; L2 refers to lag at time, t-2
* p<0.05; ** p<0.01; *** p<0.001

Research Question #3: Assessing Degree Production Efficiency

In the final stage of the analysis, I generated technical efficiency scores for the engineering schools in the analytic sample to assess the extent to which these institutions maximized degree output for URMs and African Americans. As discussed in Chapter 3, the efficiency scores were based on a stochastic frontier analysis (SFA) of the log-log functional form of the baseline production model of engineering bachelor's degrees by race/ethnicity. In order to determine whether a time-invariant or time-varying SFA model was appropriate, I estimated both models and compared the estimates obtained from each. Although not shown, the results of the time-varying SFA models suggested little change over time (i.e., the limited 7-year sample period) in institutions' efficiency scores. Likewise, the coefficient estimates for the time-varying SFA models were very close to the estimates obtained for the time-invariant models. Therefore, it was appropriate to assume no time-variation in the degree to which engineering schools maximized bachelor's degree output for URMs generally, and African Americans specifically. The statistical significance of the SFA estimates obtained for the time-invariant model, which are presented in Table 4.15, were consistent with the basic fixed effects regression estimates obtained for the full sample (Table 4.4).

Table 4.14 Stochastic frontier production model estimates by race/ethnicity for the full analytic sample.

	URM Students	Black Students
Faculty Inputs		
Log proportion non-TTT faculty	-0.03	-0.01
	(0.02)	(0.04)
Log proportion research faculty	-0.03	-0.09**
	(0.02)	(0.03)
Log faculty-student ratio	0.32***	0.21
	(0.06)	(0.12)
Log proportion URM faculty	0.03	0.00
	(0.03)	(0.06)
Log proportion female faculty	-0.01	-0.15*
	(0.04)	(0.07)
Log eng. research expenditures per FTE	-0.03	0.08
	(0.02)	(0.05)
Student Characteristics		
Log URM FTE	0.84***	0.58***
	(0.03)	(0.10)
Log total FTE	0.09*	0.04
	(0.04)	(0.09)

Table 4.14 (Cont.) Stochastic frontier production model estimates by race/ethnicity for the full analytic sample.

	URM Students	Black Students
Log proportion female B.S.	0.25***	0.18
	(0.05)	(0.10)
Log proportion URM FTE†	0.00	0.00
	(.)	(.)
Observations	916	867
Institutions	190	187

Notes: Standard errors in parentheses
†Dropped automatically due to collinearity.
* p<0.05; ** p<0.01; *** p<0.001

Table 4.15 shows that, on average, engineering schools were 84% efficient in the production of bachelor's degrees to URM students, or operated with 16% technical inefficiency. And the maximum efficiency achieved by any institution was 95% (note, again, that the model assumes constant efficiency within each institution over the seven-year period). However, engineering schools were, on average, only 62% efficient (38% inefficient) in the production of bachelor's degrees to Black students. The maximum efficiency achieved by any institution with respect to Black students was 90%.

Table 4.15 Descriptive statistics for technical efficiency (TE) estimates for time-invariant SFA degree production models.

	Observations	Mean TE	Std. Dev.	Min	Max
URM Students	2268	0.84	0.12	0.29	0.95
Black Students	2268	0.62	0.27	0.03	0.90

To further unpack the SFA results, I decided to examine the notion of "top degree producers" with respect to URM and African American engineering baccalaureates. First, I identified the top 50 producers of URM engineering baccalaureates in the sample by ranking institutions on the total number of engineering bachelor's degrees conferred to URMs over the period 2005 to 2011. Next, I ranked these top producers by their technical efficiency scores to assess the extent to which they had maximized their degree output for URMs. I used the same procedure to assess degree production for Black students.

Table 4.16 summarizes degree output and efficiency scores for the top engineering bachelor's degree producers for URMs and African Americans during the sample period. On average, the top 50 producers conferred 679 bachelor's degrees to URMs with 87% efficiency and 278 bachelor's degrees to African Americans with 63% efficiency, respectively, between 2005 and 2011.

Table 4.16 Average number of degrees and efficiency scores for top 50 engineering bachelor's degree producers by student race/ethnicity, 2005 to 2011,

	N	Mean	Std. Dev.	Min	Max
Number of bachelor's degrees, 2005-2011					
URM Students	52	678.75	361.67	349	2333
Black Students	58	277.55	184.93	134	1091
Technical efficiency scores					
URM Students	52	0.87	0.07	0.59	0.95
Black Students	58	0.63	0.19	0.17	0.90

Table 4.17 provides another way to frame the results of the efficiency analysis – presenting side-by-side rankings of institutions by absolute numbers of degrees and degree production efficiency. These data show that 56% of top producers are 90% or more efficient in producing URM baccalaureate engineers. Eighty-five percent are 80% or more efficient in bachelor's degree production for URMs. It is also worth noting that the top 3 URM baccalaureate producers in the sample – Florida International University, University of Florida, and Georgia Tech – were also the top 3 in terms of efficiency. However, the University of Texas at El Paso ranked 4th in terms of the absolute number of engineering bachelor's degrees awarded to URMs but 12th in terms of efficiency (although still more than 90% efficient). Likewise, the University of Michigan ranked 4th in terms of efficient production of URM engineering baccalaureates but 20th in terms of the absolute number of engineering bachelor's degrees awarded to URM students. George Mason University was 8th in efficiency but 44th in absolute numbers of degrees conferred to URMs. These patterns suggest that best practices in engineering bachelor's degree production might be identified within a range of institutions that may or may not include the very top producers in terms of absolute numbers of degrees conferred.

Table 4.17 Top 50 producers of engineering bachelor's degrees to URM students, by absolute number of degrees and technical efficiency (TE), 2005 to 2011.

Rank B.S.	Institution	# of B.S.	Rank TE	Institution	TE (%)
1	Florida International University	2333	1	Georgia Institute of Technology-Main Campus	94.61
2	University of Florida	1414	2	Florida International University	94.34
3	Georgia Institute of Technology-Main Campus	1361	3	University of Florida	93.96
4	The University of Texas at El Paso	1283	4	University of Michigan-Ann Arbor	93.81
5	California State Polytechnic University-Pomona	1197	5	University of California-Berkeley	93.26
6	North Carolina A & T State University	1115	6	Texas A & M University-Kingsville	92.91
7	The University of Texas at Austin	1062	7	University of Central Florida	92.90
8	Texas A & M University-College Station	1052	8	George Mason University	92.88
9	New Jersey Institute of Technology	980	9	New Jersey Institute of Technology	92.85
10	University of Central Florida	979	10	University of Maryland-College Park	92.81
11	Massachusetts Institute of Technology	813	11	University of California-San Diego	91.77
12	New Mexico State University-Main Campus	796	11	California State University-Northridge	91.77
13	Florida Agricultural and Mechanical University	774	11	California Polytechnic State University-San Luis Obispo	91.77
14	Arizona State University	752	11	Southern University and A & M College	91.77
15	Prairie View A & M University	732	11	University of Miami	91.77
16	California Polytechnic State University-San Luis Obispo	722	11	Rutgers University-New Brunswick	91.77
17	CUNY City College	721	11	Massachusetts Institute of Technology	91.77
18	North Carolina State University at Raleigh	716	11	San Jose State University	91.77
19	The University of Texas at San Antonio	679	12	The University of Texas at El Paso	90.98
20	University of Michigan-Ann Arbor	667	13	Texas Tech University	90.93
21	University of Maryland-College Park	658	14	Rensselaer Polytechnic Institute	90.88

Table 4.17 (Cont.) Top 50 producers of engineering bachelor's degrees to URM students, by absolute number of degrees and technical efficiency (TE), 2005 to 2011.

Rank B.S.	Institution	# of B.S.	Rank TE	Institution	TE (%)
22	Alabama A & M University	615	15	California State Polytechnic University-Pomona	90.83
23	University of South Florida-Main Campus	611	16	The University of Texas-Pan American	90.78
24	Texas A & M University-Kingsville	605	17	Florida Atlantic University	90.69
25	University of Houston	604	18	North Carolina State University at Raleigh	90.12
26	University of Arizona	573	19	University of Illinois at Chicago	89.93
27	The University of Texas-Pan American	568	20	University of Arizona	89.92
28	Southern University and A & M College	532	21	Virginia Polytechnic Institute and State University	89.71
29	Florida Atlantic University	527	22	University of Southern California	89.64
30	California State University-Long Beach	515	23	University of New Mexico-Main Campus	88.97
31	Rutgers University-New Brunswick	492	24	Prairie View A & M University	88.86
32	Stanford University	491	25	California State University-Long Beach	88.78
33	Virginia Polytechnic Institute and State University	482	26	CUNY City College	88.73
34	University of New Mexico-Main Campus	475	27	University of South Florida-Main Campus	88.21
35	University of California-San Diego	473	28	The University of Texas at Austin	88.02
36	Morgan State University	470	29	Alabama A & M University	87.12
37	Texas Tech University	468	30	Pennsylvania State University-Main Campus	86.75
38	Rensselaer Polytechnic Institute	451	31	New Mexico State University-Main Campus	86.30
39	San Jose State University	436	32	Morgan State University	85.38
39	University of Illinois at Chicago	436	33	The University of Texas at San Antonio	83.95
39	University of Illinois at Urbana-Champaign	436	34	Texas A & M University-College Station	81.51
40	University of Miami	417	35	North Carolina A & T State University	80.76
41	Howard University	412	36	Arizona State University	80.17
42	University of California-Berkeley	411	37	Howard University	79.56

Table 4.17 (Cont.) Top 50 producers of engineering bachelor's degrees to URM students, by absolute number of degrees and technical efficiency (TE), 2005 to 2011.

Rank B.S.	Institution	# of B.S.	Rank TE	Institution	TE (%)
43	University of Southern California	404	38	University of Illinois at Urbana-Champaign	79.46
44	George Mason University	391	39	University of Oklahoma Norman Campus	79.06
45	The University of Texas at Arlington	390	40	University of Houston	78.94
46	Pennsylvania State University-Main Campus	369	41	Tennessee State University	76.44
47	California State University-Northridge	368	42	Florida Agricultural and Mechanical University	75.76
48	Tennessee State University	362	43	The University of Texas at Arlington	72.67
49	University of Oklahoma Norman Campus	356	44	Stanford University	71.20
50	University of California-Davis	349	45	University of California-Davis	59.19

Compared to the production of underrepresented minority baccalaureate engineers, top producers are considerably less efficient when it comes to Black students specifically. Table 4.18 shows that only 24 out of 58 engineering schools (41%) are 70% or more efficient in the production of Black engineers, whereas only a single top producer operated at less than 70% efficiency with respect to URM engineers collectively. In fact, 15 out of 58 (26%) top producers are less than 50% efficient in the production of Black engineering baccalaureates.

Table 4.18 also highlights the role of HBCUs in the production of Black engineers. North Carolina A&T was both the most productive and the most efficient institution in producing African American baccalaureate engineers. Moreover, of the seven HBCUs that were among the top 10 producers, five showed up among the top 10 in terms of efficiency – North Carolina A&T University, Alabama A&M University, Prairie View A&M University, and Morgan State University. This result is noteworthy not only because HBCUs make up just 3% of ABET-accredited institutions but also because HBCUs have experienced substantial declines in the numbers of engineering degrees conferred to Black students in recent years.

While it might seem intuitive that historically Black colleges and universities would be a fruitful place to look for best practices in producing Black baccalaureate engineers (the previous discussion suggests this is still true even despite recent declines in degree output), Table 4.18 highlights other promising avenues that might be less intuitive. For example, Washington University in St. Louis was 50th in terms of the absolute number of bachelor's degrees conferred to African Americans but 5th in efficiency. The University of South Carolina-Columbia was 35th and 5th in number of degrees to African Americans and efficiency, respectively. And the University of Minnesota-Twin Cities was 39th in absolute degrees to African Americans but 7th in efficiency.

Table 4.18 Top 50 producers of engineering bachelor's degrees to BLACK students, by absolute number of degrees and technical efficiency, 2005 to 2011.

Rank B.S.	Institution	# of B.S.	Rank TE	Institution	TE (%)
1	North Carolina A & T State University	1091	1	North Carolina A & T State University	89.58
2	Georgia Institute of Technology-Main Campus	811	2	Alabama A & M University	88.29
3	Prairie View A & M University	690	3	Prairie View A & M University	87.82
4	Alabama A & M University	615	4	University of the District of Columbia	86.85
5	Florida Agricultural and Mechanical University	557	5	Washington University in St Louis	86.57
6	Southern University and A & M College	532	5	University of South Carolina-Columbia	86.57
7	North Carolina State University at Raleigh	468	5	Rutgers University-New Brunswick	86.57
8	Morgan State University	463	5	Massachusetts Institute of Technology	86.57
9	University of Maryland-College Park	442	5	Southern University and A & M College	86.57
10	Howard University	412	6	Georgia Institute of Technology-Main Campus	86.05
11	New Jersey Institute of Technology	371	7	University of Minnesota-Twin Cities	85.45
12	University of Florida	367	8	Indiana University-Purdue University-Indianapolis	84.13
13	Tennessee State University	358	9	University of Michigan-Ann Arbor	83.28
14	University of Michigan-Ann Arbor	354	10	Morgan State University	82.74
15	Tuskegee University	345	11	Tuskegee University	80.80
16	Florida International University	340	12	Auburn University	79.48
17	CUNY City College	297	13	Florida Agricultural and Mechanical University	79.41
18	University of Central Florida	285	14	The University of Tennessee	77.66
19	Virginia Polytechnic Institute and State University	284	15	University of Maryland-College Park	77.11
20	Massachusetts Institute of Technology	273	16	Tennessee State University	76.67
21	Clemson University	247	17	North Carolina State University at Raleigh	75.78

Table 4.18 (Cont.) Top 50 producers of engineering bachelor's degrees to BLACK students, by absolute number of degrees and technical efficiency, 2005 to 2011.

Rank B.S.	Institution	# of B.S.	Rank TE	Institution	TE (%)
22	Auburn University	241	18	Virginia Commonwealth University	74.70
23	Rutgers University-New Brunswick	240	19	University of Virginia-Main Campus	73.82
24	Florida Atlantic University	236	20	Howard University	73.03
25	Indiana University-Purdue University-Indianapolis	228	21	University of North Carolina at Charlotte	66.58
26	University of South Florida-Main Campus	220	22	University of Illinois at Chicago	66.55
27	Louisiana State University and A & M College	214	23	Stony Brook University	65.80
28	Old Dominion University	213	24	Old Dominion University	64.80
29	Drexel University	203	25	Pennsylvania State University-Main Campus	64.54
30	Missouri University of Science and Technology	202	26	Rensselaer Polytechnic Institute	63.92
31	Ohio State University-Main Campus	195	27	Rochester Institute of Technology	62.48
32	Wayne State University	192	28	Drexel University	61.27
33	Stanford University	189	29	Virginia Polytechnic Institute and State University	60.54
33	Mississippi State University	189	30	University of Maryland-Baltimore County	58.56
34	George Mason University	187	31	New Jersey Institute of Technology	58.25
35	University of South Carolina-Columbia	185	32	Florida International University	56.59
36	University of North Carolina at Charlotte	181	33	University of Pittsburgh-Pittsburgh Campus	56.59
37	Pennsylvania State University-Main Campus	167	34	George Mason University	56.44
38	The University of Alabama	165	35	Missouri University of Science and Technology	52.79
38	Rensselaer Polytechnic Institute	165	36	Mississippi State University	52.46
39	University of Minnesota-Twin Cities	162	37	The University of Alabama	52.24
40	University of Virginia-Main Campus	160	38	Louisiana Tech University	52.02
41	Michigan State University	157	39	Clemson University	51.00

Table 4.18 (Cont.) Top 50 producers of engineering bachelor's degrees to BLACK students, by absolute number of degrees and technical efficiency, 2005 to 2011.

Rank B.S.	Institution	# of B.S.	Rank TE	Institution	TE (%)
41	Stony Brook University	157	40	CUNY City College	47.91
41	The University of Tennessee	157	41	Ohio State University-Main Campus	47.83
42	Rochester Institute of Technology	156	42	University of Memphis	47.77
43	Texas A & M University-College Station	154	43	Louisiana State University and A & M College	45.18
44	University of Memphis	151	44	Florida Atlantic University	44.65
44	The University of Texas at Austin	151	45	University of Central Florida	42.34
45	University of Maryland-Baltimore County	149	46	Wayne State University	42.19
46	The University of Texas at Arlington	148	47	University of South Florida-Main Campus	41.24
46	University of Pittsburgh-Pittsburgh Campus	148	48	University of Florida	39.72
47	University of the District of Columbia	147	49	Michigan State University	39.32
47	Louisiana Tech University	147	50	The University of Texas at Arlington	32.38
48	University of Illinois at Chicago	137	51	Stanford University	31.84
49	Virginia Commonwealth University	135	52	University of Illinois at Urbana-Champaign	25.82
50	University of Illinois at Urbana-Champaign	134	53	The University of Texas at Austin	18.41
50	Washington University in St Louis	134	54	Texas A & M University-College Station	17.08

CHAPTER 5 – CONCLUSIONS

In this concluding chapter, I summarize the major findings and implications of the study. I discuss the contributions of the study to the broader STEM higher education literature. Finally, I end the chapter by offering recommendations for institutional and public policy.

Summary of Findings

In this study, I examined variations in engineering bachelor's degree production by student race/ethnicity and institutional context, with particular attention to possible differential relationships between faculty predictors and degree production. Using fixed effects linear regression within a higher education production function framework, I developed baseline models of the effects of faculty inputs on bachelor's degree production by student race/ethnicity and institutional context as well as alternative models that included selected capital and broad institutional input measures. I also estimated an alternative dynamic panel model of engineering degree production to relax assumptions related to the fixed effects models. Finally, I conducted an efficiency analysis to test the fundamental assumption of production functions – that firms (i.e., engineering schools) maximize output (i.e., bachelor's degrees). These analyses yielded numerous findings, which are summarized next.

Variations in inputs and outputs at engineering schools and colleges (RQ# 1). Descriptive analysis of faculty inputs and engineering degree output for all students, URM students, and Black students revealed variations in these measures between institutions by institutional control, selectivity, Carnegie classification, and HBCU status over the period from 2005 to 2011. The degree of change in the proportion of non-tenured/tenure-track engineering teaching faculty varied across categories of institutional context. The proportion of research faculty generally increased across all institutions (to varying degrees), while the engineering faculty-to-student ratio generally decreased (also to varying degrees). Tenured and tenure-track engineering faculty grew more diverse, with increasing shares of URM, Black, and female faculty at all institutional types. Engineering research expenditures more than doubled in baccalaureate institutions but were either subject to much smaller swings or generally stable in other institutional settings.

Corroborating descriptive reports about national trends in engineering bachelor's degree attainment (National Action Council for Minorities in Engineering, 2011; National Science Foundation, 2011b; Yoder, 2012), this study showed that from 2005 to 2011, the number of engineering bachelor's degrees conferred to all students and URM students increased 10% and 18% respectively. And most of the growth in engineering bachelor's degree production for URMs occurred in public institutions, highly competitive institutions, and master's institutions. At the same time, engineering bachelor's degree awards to Black students declined 10%, but less so at highly competitive institutions (2% decline) and at an especially high rate at HBCUs (30% decline).

That the decline in African American engineering bachelor's degree production is so large within HBCUs is particularly troublesome given the past contributions of

HBCUs in the growth of engineering attainment among Black students from the early 1970s through the late 1990s, both through the handful of engineering programs at HBCUs and through dual degree partnerships with non-HBCUs (Weinberger, 2011). Likewise, available research suggests that Black engineering students at HBCUs have more positive perceptions of their academic climates and are less likely to switch to non-STEM majors compared to their peers at non-HBCUs (Brown, Morning, & Watkins, 2005; Newman, 2011). At the same time, this study showed that HBCUs, which represent only 3% of ABET-accredited engineering schools/colleges, remain among the most productive and most technically efficient producers of Black engineers. Specifically, seven HBCUs were among the top 10 producers of engineering bachelor's degrees for Black students and five of the seven were among the top 10 in terms of efficiency. This finding indicates that HBCUs are not performing less well with the inputs they have; rather, for some reason, they are enrolling precipitously fewer engineering students. Given their historic leading role in educating Black engineers, future research might investigate HBCUs' apparent enrollment problem to uncover further insights into the engineering attainment issue facing African Americans.

Which faculty inputs matter for whom and in which contexts (RQ# 2)? Fixed effects regression models of engineering degree production uncovered differential relationships between selected faculty inputs and degree outputs by student race/ethnicity and institutional context. Figure 4.1 graphically synthesizes key findings along four dimensions. Shaded cells indicate statistically significant predictors and the institutional contexts in which the predictors were significant. The +/- and letters inside the cells indicate for whom (all students [A], URM students [U], or Black students [B]) a positive or negative relationship was detected.

Figure 5.1 Summary matrix of faculty input effects by institutional context and student race/ethnicity.

	Institutional Control			Selectivity (Comp. = Competitive)				Carnegie 2010		
	Private	Public	Land Grant	Highly Comp.	Very Comp.	Comp.	Less Comp.	Doctorate/ Research	Master's	HBCU
Proportion Non-TTT Faculty				**(-)B**						
Proportion Research Faculty	**(-)U**	**(-)A (+)U**			**(-)A**			**(-)A (-)B**		**(-)B**
Faculty-student Ratio	**(+)A (+)U (+)B**			**(+)A (+)U (+)B**				**(+)A (+)U**		
Proportion URM Faculty			**(+)B**				**(+)U (+)B**			
Proportion Female Faculty				**(-)B**			**(-)U**	**(-)B**		
Engr. Research Expenditures									**(-)A**	
Proportion Black Faculty	**(+)B**		**(+)B**							

Notes:
Shading indicates statistical significance of estimated effect;
Direction of relationship in parentheses;
A = engineering bachelor's degree output for all students;
U = engineering bachelor's degrees output for URM students;
B = engineering bachelor's degrees output for Black students.

The only faculty inputs that predicted degree output in at least one institutional context across the three race/ethnicity categories were faculty-to-student ratio and the proportion of research faculty. Faculty-to-student ratio was consistently positively related to degree output in private institutions, highly competitive institutions, and doctorate-granting/research institutions. In each instance, the magnitude of the estimated positive effect of faculty-to-student ratio was stronger for URMs compared to all students but strongest for Black students compared to either URMs or all students. Faculty-to-student ratio was operationalized in the study as total FTE engineering faculty to total FTE undergraduate enrollment. I conducted a sensitivity analysis to determine if replacing this measure with the tenured/tenure-track only faculty-to-student ratio would change the findings and concluded that the model estimates were not sensitive to this modification (see Table A.4 in the appendix).

The proportion of research faculty was negatively related to degree output for all students, URM students, and Black students in multiple institutional contexts (i.e., public and private institutions, very competitive institutions, doctorate/research institutions, and HBCUs). This finding might suggest that, in general, greater commitments to research within these types of engineering schools might be at the expense of instructional outputs – to the extent that greater shares of the faculty are, presumably, not focused on teaching or interacting with undergraduate students. However, within public engineering schools, increasing shares of research faculty was positively related to degree output for URM students. This contradictory finding might reflect efforts at public institutions to engage undergraduates in research thereby increasing their interaction with research faculty. Regardless, further investigation is necessary to more fully explain these findings.

The engineering degree production model estimates confirmed that faculty demographics are significant predictors of degree output for underrepresented minorities and Black students specifically. First, the proportion of female tenured/tenure-track engineering faculty was negatively related to URM degree output at less competitive institutions and to Black degree output at highly competitive and doctorate-granting institutions. This finding is particularly interesting given that the proportion of female baccalaureates was associated with greater degree output for underrepresented minorities in public, highly competitive, and doctorate/research institutions. Because no prior research identified examines the links between faculty gender and student outcomes in STEM by race/ethnicity, further study is needed to understand the mechanism and implications of this statistical association.

On the other hand, increasing proportions of URM faculty was positively related to engineering bachelor's degree output for URMs and Black students at less competitive institutions and Black students at land grant institutions. Again, the magnitude of the relationship was stronger for Black students relative to URMs. I conducted a sensitivity analysis of the Black student degree output models to determine if replacing the URM-focused variables with same-race predictors would affect my findings. That is, I replaced the proportion of URM faculty with the proportion of African American faculty, URM FTE enrollment with African American FTE enrollment, etc. The findings (presented in Table A.5) were qualitatively similar in that the proportion of Black faculty was positively related to degree production for Black students. However, this relationship was detected in private institutions and land grant institutions, whereas the shares of URM faculty predicted bachelor's degrees to Black students in less competitive and land grant institutions.

Alternative models. Selected capital inputs – expenditures for engineering equipment and the share of institutional revenues from endowment, gifts, contracts, etc. – were not statistically related to engineering degree output. Although capital inputs likely have long term effects on instructional outputs, the seven-year period investigated in this study is more aptly described as the short run, over which capital inputs are relatively fixed (Paulsen & Toutkoushian, 2006). Likewise, relative to labor inputs, institutional capital inputs are not generally considered to be practical policy levers for influencing higher education output (Salerno, 2002).

The dynamic degree production models, which included lagged dependent variables, confirmed the importance of faculty-to-student ratio in predicting degree output at private institutions – with stronger estimated effects observed for Black students relative to URM students. However, due to specification differences, the dynamic estimates were not directly comparable to the basic fixed effects estimates. Still, the results suggest a need for further consideration of dynamic higher education production models.

Gaining insights from analyzing efficiencies (RQ# 3). The efficiency analysis provided evidence that there is room for all engineering institutions to increase their degree output for URM and Black students with the existing levels of selected faculty inputs. In other words, engineering schools and colleges can do more with what they already have, especially with respect to degree production for Black students. By identifying technically efficient degree producers, subsequent qualitative research could identify best practices within these institutions, instead of simply looking to institutions that confer large numbers of degrees to URMs and Blacks specifically. However, like any efficiency analysis based on an estimated higher education production function (as opposed to a "true" production function), misspecification of the production function is always a looming possibility.

Discussion

Perhaps the most important finding from this study was no finding at all. That is to say, no faculty input was predictive of degree output for every student race/ethnicity category across every institutional context. In production function language, engineering degree production technologies differ across student race/ethnicity and institutional contexts. This conclusion is important because it makes clear that broad generalizations about relationships between the faculty predictors specified in this study and engineering degree output may be problematic or unhelpful for improving institutional performance.

Nevertheless, future research would benefit from more complete, more extensive data on engineering schools and colleges. For example, as part of the Survey of Engineering and Engineering Technology Colleges, the American Society for Engineering Education currently collects information on aggregate student background characteristics (high school GPA, SAT/ACT scores, etc.); the number of degrees awarded through dual degree programs with partner institutions; numbers of graduate teaching assistants; and the availability of retention, support programs, and student organization. However, these data were largely incomplete and unusable for this study. Available research has already demonstrated links between some programmatic interventions and URM persistence in engineering, for example (e.g., Good, Haplin, & Haplin, 2002). Therefore, if the unobserved measures also varied over time within institutions, they potentially confound this study's findings. Future research might also identify other data sources, and as a result, other analytic methods to facilitate engineering education production function studies. For example, administrative data on students enrolled in engineering colleges and schools, such as the data available through the restricted Multiple-Institution Database for Investigating Engineering Longitudinal Development (MIDFIELD) project at Purdue University (MIDFIELD, 2013) would enable multi-level analyses of engineering degree production or retention.

Contribution

This study makes several contributions to the higher education literature. First, the key findings of this study provide evidence that institutional inputs (i.e., faculty predictors) are differentially related to institutional outcomes (i.e., bachelor's degree production) in a STEM discipline (i.e., engineering) both by student race/ethnicity and institutional setting. These findings have multiple policy-relevant implications given existing gaps in the knowledge and growing interest in: (a) the role of institutional predictors in students' outcomes in STEM fields, which emerging research has only recently begun to examine (e.g., Malcom, 2008; Chang, Cerna, Hans, & Sàenz, 2008;

Hurtado et al, 2009; Eagan, 2010); (b) institutional performance and accountability in higher education (Alexander, 2000; Chubin, May, & Babco, 2005); (c) access and success in STEM fields for traditionally underrepresented students (National Science Board, 2011); and (d) engineering degree production (Petroski, 2010; Augustine, 2011; Jobs Council, 2011).

Second, the study demonstrates the utility of publicly available, institutional data that up to now have not been exploited in higher education research. Use of data from the American Society of Engineering Education and the National Science Foundation enabled me to examine measures – faculty characteristics and degree completions, for example – that were specific to engineering schools and colleges. This study provided new perspectives and insights particularly because these measures have received little attention in prior studies.

Third, the methodologies employed in this study also help to advance the knowledge about STEM/higher education phenomena. The study explicitly dealt with missing data through multiple imputation, whereas existing (quantitative) STEM higher education research often neglects to even comment on missing data. The study also drew on longitudinal/panel data and appropriate econometric analysis methods, which diminished the problem of unobserved heterogeneity and provided a more direct test of a potential institutional policy lever (i.e., faculty) (Zhang, 2010). Relative to cross-sectional data, panel data have many statistically attractive properties (Woolridge, 2009; Allison, 2009; Zhang, 2010). Therefore, given the increasing availability of panel data sets, future higher education research should continue to exploit the advantages of panel data.

Fourth, the study provided clear evidence that aggregating institutions and students can obscure substantive differences in the relationships of interest. My results showed that while some faculty measures (i.e., faculty-to-student ratio and the proportion of research faculty) were statistically related to degree production for all student subgroups in some institutional settings, no faculty measures were completely equally predictive of engineering degree production across these categories. The results suggest that wherever possible, future research about and eventual solutions to the nation's STEM workforce development problems should be targeted at specific disciplines, specific student subgroups, and specific educational settings.

Policy Recommendations

This study sought to develop understanding regarding institutional levers that might offer promise for expanding student participation and success in engineering – particularly with respect to underrepresented minorities broadly, and Black students specifically. Such understanding could lead to more strategic use of resources and better-targeted interventions. The following policy recommendations, which are aimed at both institutional decision-makers and the broader engineering education community, are suggested to facilitate this understanding:

Fist, data collection and sharing efforts must be improved. Existing data collection efforts (e.g., through ASEE and the Engineering Workforce Commission

[EWC]) should include clear reporting standards and other strategies to ensure the quality and completeness of the data collected. Other efforts might be undertaken to broaden access to existing multi-institutional administrative databases (e.g., MIDFIELD) or create new ones. New and existing engineering education surveys and databases should also solicit information about program/school level expenditures for instruction, academic support, and student support services. Available research has already established a connection between institutional expenditures and institutional graduation rates (e.g., Ryan, 2004; Webber & Ehrenberg, 2010; Chen, 2012; Webber, 2012). In order to examine the potential role of expenditures (or other potentially relevant inputs) in the context of STEM fields, program-level data are needed. At the very least, institutions interested in understanding their own education production function "technologies" must collect relevant, longitudinal program and student-level data.

Second, institutions should undertake efforts to increase opportunities for meaningful engineering faculty-student interaction. That total FTE faculty-to-student ratio was generally positively related to degree production but research faculty was negatively related to degree production for URM and Black students suggests a need to increase the opportunity for meaningful interaction between engineering students and all facets of the faculty. For example, undergraduate research programs, which are typically structured to include mentoring, training in laboratory techniques, and formal presentation of results (Laursen et al., 2010) have been credited with a broad range of benefits to STEM students in general: from increased technical knowledge, laboratory, problem-solving, and presentation skills to clarification of career and post-baccalaureate educational plans (Kardash, 2000; Lopatto, 2004, 2007; Laursen et al., 2010). Concerning URM STEM students, undergraduate research reportedly increases academic performance, self-efficacy, undergraduate persistence, and graduate school enrollment (Barlow & Villarejo, 2004; Carter, Mandell, & Maton, 2009; Hurtado et al., 2007; Lopatto, 2004; Nagda et al., 1998). Therefore, undergraduate research opportunities that connect engineering students with both teaching and research faculty members might foster other potentially positive outcomes, especially for URM and Black students.

Findings from this study also echo previous findings about the importance of same-race faculty-student interactions for improving URM and Black student outcomes in STEM (for example, Fries-Britt, 1998; Fries-Britt, Younger, & Hall, 2010; Griffin, Perez, Holmes, & Mayo, 2010; Price, 2010; Cole & Espinoza, 2008; Hrabowski & Maton, 2009). Therefore, institutions and other stakeholders should seek to increase these opportunities, both with respect to existing URM faculty (e.g., through mentoring and advising) as well as through initiatives to create a new cadre of URM engineering doctorate-recipients/academic faculty.

Third, whenever possible, institutions and other stakeholders should develop targeted STEM education interventions that are based on targeted STEM education research. Despite three decades of research examining URM success in STEM, many have argued that the nil to modest gains made by URMs do not come close to mirroring the efforts (and dollars) invested (Committee on Equal Opportunities in Science and Engineering, 2004; Watson & Froyd, 2007). This lack of more substantial progress may be due, in part, to the limitations of broadly defined notions of STEM and URMs and, consequently, broadly defined interventions. This study demonstrated that even within one STEM discipline, institutional measures are not equivalently predictive of educational outcomes by student race/ethnicity or across institutional contexts. Thus, broad institutional initiatives might not be equivalently effective. Targeted approaches are needed to move the needle on this issue.

Science, technology, engineering and mathematics (STEM) fields are widely credited as the primary drivers of economic growth through innovation. And among the STEM disciplines, the contributions of engineering are universally identified as especially critical. Yet as other nations have strengthened their engineering talent pools, the United States has struggled to cultivate an engineering workforce that reflects its diversity and takes full advantage of its human capital. Reflecting this dilemma, African Americans have consistently posted the weakest persistence and bachelor's degree completion rates of all racial/ethnic groups in engineering, and by most indications, their postsecondary outcomes in engineering are worsening.

In several institutional contexts examined in this study, increasing the opportunity for student contact with engineering faculty was associated with increased bachelor's degree production. Increasing the opportunity for URM and Black students to interact with URM faculty was also associated with increased bachelor's degree production (in some institutional contexts), and especially for Black students. Rather than focusing solely on individual students' backgrounds (as STEM higher education research traditionally has), this study showed that there is clearly room to more effectively leverage institutional assets like faculty to increase engineering bachelor's degree completion among all students, underrepresented minority students, and African American students.

APPENDIX

Table A.1 Engineering schools/colleges included in the study by state.

Alabama
Alabama A & M University
University of Alabama at Birmingham
University of Alabama at Huntsville
The University of Alabama
Auburn University
University of South Alabama
Tuskegee University

Alaska
University of Alaska Anchorage
University of Alaska Fairbanks

Arizona
Arizona State University
University of Arizona
Embry-Riddle Aeronautical University-Prescott
Northern Arizona University

Arkansas
University of Arkansas at Little Rock
University of Arkansas
Arkansas State University-Main Campus
Arkansas Tech University
John Brown University

California
California Institute of Technology
California Polytechnic State University-San Luis Obispo

California (Cont.)
California State Polytechnic University-Pomona
California State University-Chico
California State University-Fresno
California State University-Fullerton
California State University-East Bay
California State University-Long Beach
California State University-Los Angeles
California State University-Northridge
California State University-Sacramento
University of California-Berkeley
University of California-Davis
University of California-Los Angeles
University of California-Riverside
University of California-San Diego
University of California-Santa Barbara
University of California-Santa Cruz
California Maritime Academy
Harvey Mudd College
Humboldt State University
Loyola Marymount University
University of the Pacific
San Diego State University
University of San Diego
San Francisco State University
San Jose State University
Santa Clara University
Stanford University
University of Southern California

Colorado
University of Colorado Denver
University of Colorado-Colorado Springs
University of Colorado Boulder
Colorado School of Mines
Colorado State University-Fort Collins
University of Denver
Colorado State University-Pueblo
United States Air Force Academy

Connecticut
University of Bridgeport
University of Connecticut
Fairfield University
University of Hartford
University of New Haven
Trinity College
United States Coast Guard Academy
Yale University

Delaware
University of Delaware

District of Columbia
Catholic University of America
University of the District of Columbia
George Washington University
Howard University

Table A.1 (Cont.) Engineering schools/colleges included in the study by state.

Florida
University of Central Florida
Embry-Riddle Aeronautical University-Daytona Beach
Florida Agricultural and Mechanical University
Florida Atlantic University
Florida Institute of Technology
Florida International University
University of Florida
University of MiamiUniversity of North Florida
University of South Florida-Main Campus

Georgia
Georgia Institute of Technology-Main Campus
University of Georgia
Mercer University

Hawaii
University of Hawaii at Manoa

Idaho
Boise State University
Idaho State University
University of Idaho

Illinois
Bradley University
University of Illinois at Chicago
University of Illinois at Urbana-Champaign
Illinois Institute of Technology
Northern Illinois University

Illinois (Cont.)
Northwestern University
Southern Illinois University Carbondale
Southern Illinois University Edwardsville

Indiana
Indiana University-Purdue University-Fort Wayne
Indiana University-Purdue University-Indianapolis
Indiana Institute of Technology
University of Notre Dame
Purdue University-Calumet Campus
Purdue University-Main Campus
Rose-Hulman Institute of Technology
Trine University
Valparaiso University

Iowa
Iowa State University
University of Iowa
Saint Ambrose University

Kansas
University of Kansas
Kansas State University
Wichita State University

Kentucky
University of Kentucky
University of Louisville
Union College
Western Kentucky University

Louisiana
Louisiana State University and A & M College
Louisiana Tech University
McNeese State University
University of New Orleans
Southern University and A & M College
University of Louisiana at Lafayette
Tulane University of Louisiana

Maine
University of Maine
University of Southern Maine

Maryland
Capitol College
Johns Hopkins University
Loyola University Maryland
University of Maryland-Baltimore County
University of Maryland-College Park
Morgan State University
United States Naval Academy

Massachusetts
Boston University
Harvard University
University of Massachusetts-Lowell
University of Massachusetts Amherst
Massachusetts Institute of Technology
Massachusetts Maritime Academy
Merrimack College
Northeastern University
Smith College

Table A.1 (Cont.) Engineering schools/colleges included in the study by state.

Massachusetts
University of Massachusetts-Dartmouth
Tufts University
Wentworth Institute of Technology
Western New England University
Worcester Polytechnic Institute

Michigan
Calvin College
University of Detroit Mercy
Ferris State University
Kettering University
Grand Valley State University
Lake Superior State University
Lawrence Technological University
University of Michigan-Ann Arbor
Michigan State University
Michigan Technological University
University of Michigan-Dearborn
Oakland University
Saginaw Valley State University
Wayne State University
Western Michigan University

Minnesota
Minnesota State University-Mankato
University of Minnesota-Twin Cities
University of Minnesota-Duluth
Saint Cloud State University
University of St Thomas
Winona State University

Mississippi
University of Mississippi
Mississippi State University

Missouri
University of Missouri-Columbia
University of Missouri-Kansas City
Missouri University of Science and Technology
Saint Louis University-Main Campus
Southeast Missouri State University
Washington University in St Louis

Montana
Carroll College
Montana Tech of the University of Montana
Montana State University

Nebraska
University of Nebraska-Lincoln

Nevada
University of Nevada-Las Vegas
University of Nevada-Reno

New Hampshire
Dartmouth College
University of New Hampshire-Main Campus

New Jersey
Fairleigh Dickinson University-Metropolitan Campus
Rowan University

New Jersey (Cont.)
Monmouth University
New Jersey Institute of Technology
Princeton University
Rutgers University-New Brunswick
Stevens Institute of Technology
The College of New Jersey

New Mexico
New Mexico Institute of Mining and Technology
University of New Mexico-Main Campus
New Mexico State University-Main Campus

New York
Alfred University
Clarkson University
Columbia University in the City of New York
Cooper Union for the Advancement of Science and Art
Cornell University
CUNY City College
Hofstra University
Manhattan College
New York Institute of Technology
Polytechnic Institute of New York University
Rensselaer Polytechnic Institute
Rochester Institute of Technology
University of Rochester
SUNY at Binghamton
Stony Brook University
SUNY College of Environmental Science and Forestry
SUNY College at Buffalo

Table A.1 (Cont.) Engineering schools/colleges included in the study by state.

New York (Cont.)
State University of New York at New Paltz
Syracuse University
United States Merchant Marine Academy
United States Military Academy
Webb Institute

North Carolina
Duke University
North Carolina A & T State University
University of North Carolina at Charlotte
North Carolina State University at Raleigh

North Dakota
North Dakota State University-Main Campus

Ohio
University of Akron Main Campus
Case Western Reserve University
University of Cincinnati-Main Campus
Cleveland State University
University of Dayton
Marietta College
Miami University-Oxford
Ohio Northern University
Ohio State University-Main Campus
Ohio University-Main Campus
University of Toledo
Wright State University-Main Campus
Youngstown State University

Oklahoma
Oklahoma Christian University
Oklahoma State University-Main Campus
University of Oklahoma Norman Campus
Oral Roberts University
University of Tulsa

Oregon
Oregon Institute of Technology
Oregon State University
Portland State University
University of Portland

Pennsylvania
Bucknell University
Carnegie Mellon University
Drexel University
Gannon University
Grove City College
Lafayette College
Lehigh University
Messiah College
Pennsylvania State University-Erie-Behrend College
Pennsylvania State University-Harrisburg
Pennsylvania State University-Main Campus
University of Pennsylvania
Philadelphia University
University of Pittsburgh-Pittsburgh Campus
Swarthmore College
Temple University

Pennsylvania (Cont.)
Villanova University
Widener University-Main Campus
Wilkes University
York College Pennsylvania

Rhode Island
Brown University
University of Rhode Island
Roger Williams University

South Carolina
Citadel Military College of South Carolina
Clemson University
University of South Carolina-Columbia

South Dakota
South Dakota School of Mines and Technology
South Dakota State University

Tennessee
Christian Brothers University
University of Memphis
The University of Tennessee at Chattanooga
The University of Tennessee
The University of Tennessee-Martin
Tennessee State University
Tennessee Technological University
Vanderbilt University

Table A.1 (Cont.) Engineering schools/colleges included in the study by state.

Texas
Baylor University
University of Houston
Lamar University
LeTourneau University
University of North Texas
The University of Texas-Pan American
Prairie View A & M University
Rice University
Southern Methodist University
Texas A & M University-Kingsville
Texas A & M University-Galveston
Texas A & M University-College Station
The University of Texas at Arlington
The University of Texas at Austin
The University of Texas at Dallas
The University of Texas at El Paso
The University of Texas at Tyler
Texas Christian University
The University of Texas at San Antonio
Texas Tech University
Trinity University

Utah
Brigham Young University-Provo
Utah State University
University of Utah

Vermont
Norwich University
University of Vermont

Virginia
George Mason University
Old Dominion University
Virginia Polytechnic Institute and State University
Virginia Commonwealth University
University of Virginia-Main Campus
Virginia Military Institute

Washington
Gonzaga University
Saint Martin's University
Seattle Pacific University
Seattle University

Washington (Cont.)
Walla Walla University
Washington State University
University of Washington-Seattle Campus

West Virginia
West Virginia University Institute of Technology
West Virginia University

Wisconsin
Marquette University
Milwaukee School of Engineering
University of Wisconsin-Stout
University of Wisconsin-Madison
University of Wisconsin-Milwaukee
University of Wisconsin-Platteville

Wyoming
University of Wyoming

Figure A.1 Histograms of model variables before and after log transformations: number of bachelor's degrees to all students, URM students, and African American students.

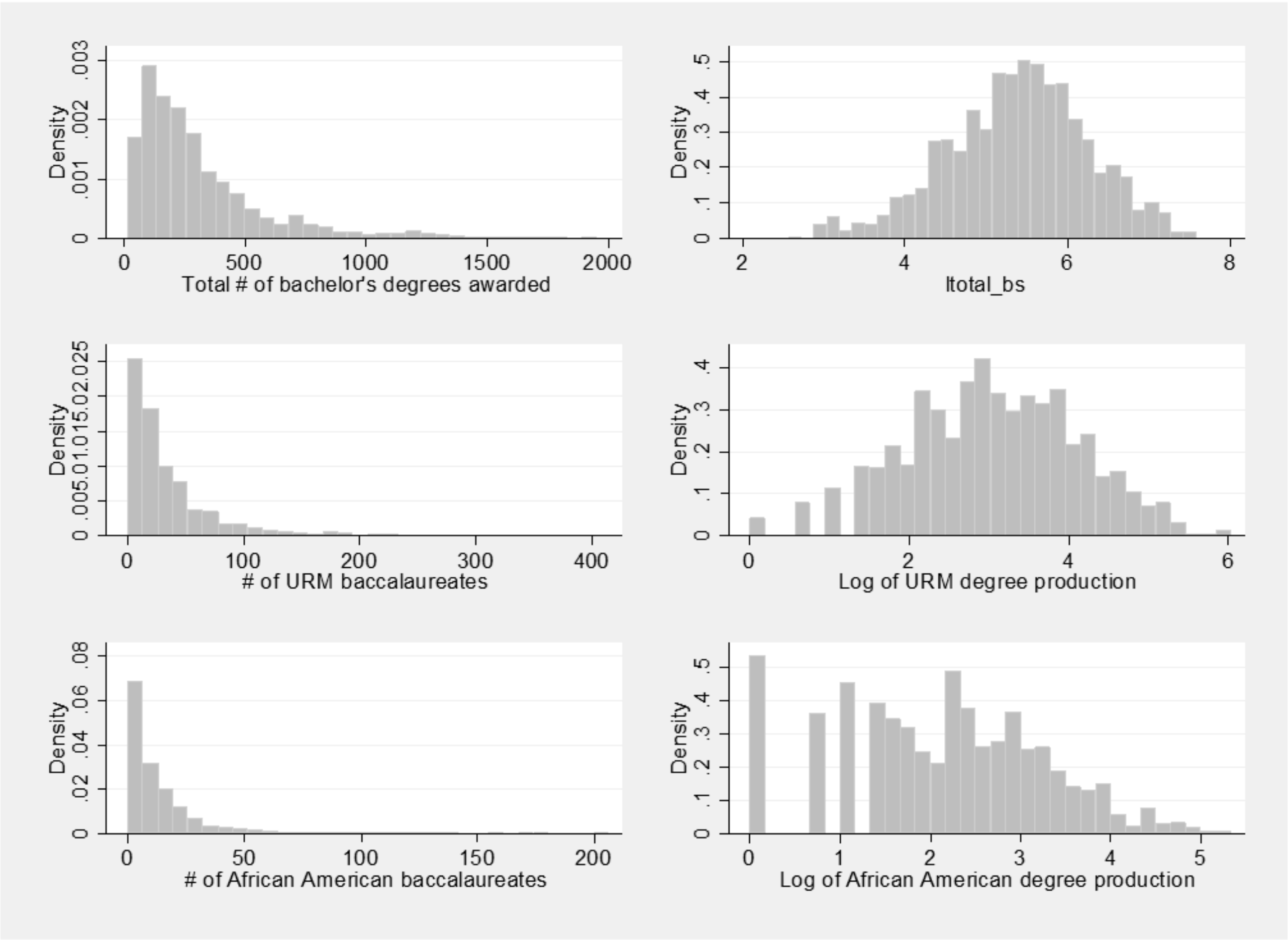


Figure A.2 Histograms of model variables before and after log transformations: total FTE engineering undergraduates, URM FTE engineering undergraduates, number of full-time

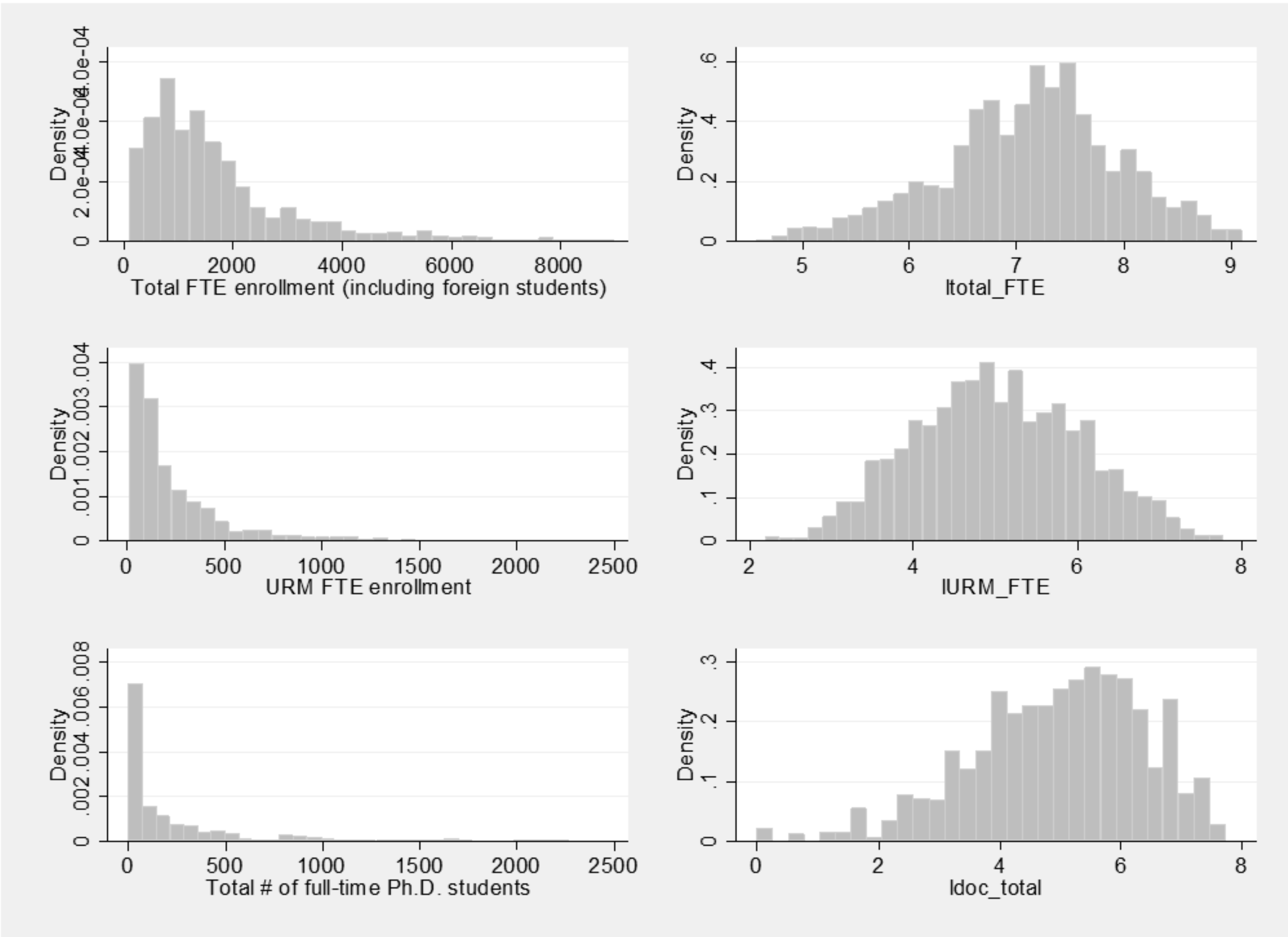


Table A.2 Decomposed descriptive statistics for outcome and explanatory variables, computed to confirm variation over time.

Variable		Mean	Std. Dev.	Min	Max	Observations
B.S. degrees to all students	overall	249	264	1	1950	N = 2266
	between		262	3	1733	N = 324
	within		34	30	516	T-bar = 6.99
B.S. degrees to URM students	overall	28	40	0	414	N = 2221
	between		39	0	333	n = 324
	within		9	-58	109	T-bar = 6.85
B.S. degrees to Black students	overall	11	19	0	206	N = 2221
	between		18	0	156	n = 324
	within		5	-39	63	T-bar = 6.85
Proportion non-TTT faculty	overall	0.14	0.14	0	0.91	N = 2191
	between		0.10	0	0.65	n = 323
	within		0.09	-0.26	0.83	T-bar = 6.78
Proportion research faculty	overall	0.09	0.13	0	0.80	N = 2191
	between		0.11	0	0.66	n = 323
	within		0.06	-0.35	0.48	T-bar = 6.78
Faculty-student ratio	overall	0.10	0.11	0.00	1.60	N = 2169
	between		0.10	0.02	1.16	n = 321
	within		0.04	-0.21	0.54	T-bar = 6.76

Table A.2 (Cont.) Decomposed descriptive statistics for outcome and explanatory variables, computed to confirm variation over time.

Variable		Mean	Std. Dev.	Min	Max	Observations
Proportion URM faculty	overall	0.06	0.08	0	1	N = 2137
	between		0.08	0	0.69	n = 318
	within		0.03	-0.11	0.66	T-bar = 6.72
Engineering research expenditures per FTE	overall	14292	30482	0	479,492	N = 1899
	between		28634	0	401,391	n = 299
	within		6594	-57,164	114,553	T-bar = 6.35

Table A.3 Hausman Test comparing fixed effects and random effects estimates of log engineering degree production for URM students.

Variables	Coefficients FE estimates (b)	 RE estimates (B)	Difference (b-B)	$(\mathrm{diag}(V_b - V_B))^{1/2}$ S.E.
Proportion non-TTT faculty	-0.06	0.00	-0.06	0.09
Proportion research faculty	0.14	-0.24	0.38	0.10
Faculty-student ratio	0.86	1.38	-0.51	0.27
Proportion URM faculty	0.22	0.44	-0.21	0.28
Proportion female faculty	-0.24	-0.57	0.33	0.34
Log eng. research exp per FTE	0.04	0.01	0.03	0.04
Log URM FTE	0.79	0.83	-0.04	0.08
Log total FTE	-0.29	0.02	-0.31	0.12
Proportion URM Ph.D.	0.33	0.48	-0.15	0.14
Log total Ph.D.	0.03	0.07	-0.04	0.03
Proportion female B.S.	0.56	0.85	-0.30	0.21
Proportion URM FTE	-3.52	-0.05	-3.46	0.69

Notes: Hausman test computation:

b = consistent under Ho and Ha; obtained from fixed effects regression
B = inconsistent under Ha, efficient under Ho; obtained from random effects regression
Test: Ho: difference in coefficients not systematic
chi2(12) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 122.56
Prob>chi2 = 0.0000
Therefore, under the current specification, the null hypothesis that the faculty effects are adequately modeled by a random-effects model is resoundingly rejected.

Table A.4 Sensitivity analysis: Faculty-to-student ratio (Fixed effects estimates of log engineering degree bachelor's degrees to URM students using pooled sample of institutions and 20 imputed data sets).

Variables	Model 1	Model 2
Faculty Inputs		
Proportion non-TTT faculty	-0.09	0.10
	(0.17)	(0.13)
Proportion of research faculty	0.18	0.30
	(0.19)	(0.18)
Faculty-student ratio (ALL faculty)	0.87	
	(0.52)	
Faculty-student ratio (tenured/tenure-track only)		1.95
		(1.90)
Proportion URM faculty	0.08	0.06
	(0.37)	(0.37)
Proportion female faculty	-0.12	-0.05
	(0.54)	(0.53)
Log eng. Research expenditures per FTE	0.04	0.04
	(0.05)	(0.05)
Student Characteristics		
Log URM FTE	0.75***	0.76***
	(0.21)	(0.21)
Log total FTE	-0.27	-0.24
	(0.26)	(0.28)
Proportion URM Ph.D.	0.36	0.37
	(0.36)	(0.35)
Log total Ph.D.	0.03	0.03
	(0.05)	(0.05)
Proportion female B.S.	0.86*	0.88*
	(0.40)	(0.41)
Proportion URM FTE	-3.55**	-3.58**
	(1.14)	(1.15)
Observations	1200	1200
Institutions	182	182

Notes: Standard errors in parentheses
legend: * p<0.05; ** p<0.01; *** p<0.001

Table A.5 Sensitivity analysis: Same-race predictors (Fixed effects estimates of log engineering degree bachelor's degrees to BLACK students by institutional context using 20 imputed data sets).

Variables	All Inst.	Institutional Control: Private	Institutional Control: Public	Institutional Control: Land Grant	Selectivity: Highly Comp-etitive	Selectivity: Very Comp-etitive	Selectivity: Comp-etitive	Selectivity: Less Comp-etitive	2010 Carnegie Classification: Doctoral/ Research	2010 Carnegie Classification: Master's	2010 Carnegie Classification: HBCU
Faculty Characteristics											
Proportion non-TTT	-0.16	-0.26	0.11	-0.42	-0.49	0.34	0.16	0.72	-0.34	0.25	-0.24
faculty	(0.21)	(0.25)	(0.28)	(0.70)	(0.28)	(0.45)	(0.37)	(1.25)	(0.23)	(0.81)	(0.37)
Proportion research	-0.39	-0.39	-0.30	-0.73	-0.26	-0.75	-0.03	-0.76	-0.49*	1.12	-1.65*
faculty	(0.23)	(0.37)	(0.26)	(0.68)	(0.27)	(0.45)	(0.40)	(1.07)	(0.24)	(0.92)	(0.58)
Faculty-student ratio	1.13	1.85*	0.20	3.32	1.80*	-0.11	-0.01	-2.61	1.46*	-2.53	0.58
	(0.74)	(0.83)	(0.74)	(4.15)	(0.75)	(0.98)	(1.71)	(8.78)	(0.69)	(6.45)	(2.48)
Proportion Black	0.92	1.40*	0.10	4.96*	0.51	-3.54	-0.19	2.64	-0.21	-2.47	0.72
faculty	(0.53)	(0.63)	(1.51)	(2.46)	(1.54)	(2.56)	(0.76)	(3.31)	(1.26)	(5.42)	(1.05)
Proportion female	-1.85*	-2.69	-0.86	-0.57	-3.53*	-2.69	0.95	-3.81	-2.15*	0.77	-1.37
faculty	(0.84)	(1.41)	(0.99)	(2.09)	(1.41)	(1.65)	(1.36)	(3.15)	(0.89)	(2.72)	(2.29)
Log eng. Research	-0.05	-0.18	0.02	0.24	-0.03	-0.10	-0.09	0.23	-0.09	-0.07	0.74
expenditures per FTE	(0.07)	(0.15)	(0.07)	(0.20)	(0.10)	(0.17)	(0.11)	(0.43)	(0.07)	(0.17)	(0.34)
Student Characteristics											
Log Black FTE	0.12	0.34	-0.16	-0.46*	0.20	-0.30	0.30	0.31	0.22	-1.10	1.77
	(0.15)	(0.20)	(0.16)	(0.19)	(0.25)	(0.32)	(0.28)	(0.48)	(0.14)	(0.56)	(1.36)
Log total FTE	0.19	0.11	0.35	0.87	0.50	0.43	-0.57	0.18	0.11	1.48	-0.25
	(0.23)	(0.40)	(0.24)	(0.56)	(0.40)	(0.40)	(0.46)	(0.97)	(0.21)	(0.91)	(1.56)
Proportion Black	0.84	1.07	0.55	1.03	-1.95	1.30	0.61	-0.82	1.65**	-0.46	0.53
Ph.D.	(0.67)	(1.08)	(0.67)	(0.62)	(4.31)	(1.09)	(0.74)	(1.32)	(0.55)	(0.97)	(0.53)

Table A.5 (Cont.) Sensitivity analysis: Same-race predictors (Fixed effects estimates of log engineering degree bachelor's degrees to BLACK students by institutional context using 20 imputed data sets).

		Institutional Control			Selectivity				Carnegie Classification		
Variables	All Inst.	Private	Public	Land Grant	Highly Comp-etitive	Very Comp-etitive	Comp-etitive	Less Comp-etitive	Doctoral/ Research	Master's	HBCU
Log total Ph.D.	-0.01	0.17	-0.05	-0.07	0.06	-0.08	0.18	-0.56**	-0.04	0.03	0.11
	(0.06)	(0.11)	(0.07)	(0.15)	(0.12)	(0.10)	(0.10)	(0.18)	(0.06)	(0.21)	(0.10)
Proportion female	0.56	0.75	0.34	-1.82	1.56	-0.74	0.32	1.75	0.63	1.20	-0.39
B.S.	(0.52)	(0.94)	(0.61)	(1.30)	(0.84)	(1.57)	(0.72)	(1.78)	(0.53)	(2.15)	(1.02)
Proportion Black FTE	-1.92	-4.30*	2.03	3.06	-1.00	2.12	-3.37	-4.30	-1.95	3.69	-4.54
	(1.62)	(1.91)	(1.83)	(2.52)	(6.48)	(5.64)	(1.81)	(3.49)	(1.92)	(5.45)	(3.06)
R^2, within	.024	.118	.012	.063	.096	.066	.039	.217	.041	.266	.616
Observations	1132	308	824	314	421	301	337	73	1040	74	48
Institutions	182	49	133	52	63	51	54	14	164	15	7

Notes: Standard errors in parentheses
legend: * p<0.05; ** p<0.01; *** p<0.001
This set of analyses includes comparisons across 9 institutional contexts, which increases the probability of Type I errors.

BIBLIOGRAPHY

ABET (2012). Find accredited programs. Retrieved from http://main.abet.org/aps/Accreditedprogramsearch.aspx

Abramovitz, M. (1986). Catching up, forging ahead, and falling behind. *Journal of Economic History 46*(2), 385-406.

Adelman, C. (1998). *Women and men of the engineering path: A model for analyses of undergraduate careers*. Washington, DC: U.S. Department of Education, National Institute of Education Sciences.

Aigner, D., Lovell, C. A. L., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of econometrics*, *6*(1), 21-37.

Allen, W.R. (1992). The color of success: African American college student outcomes at predominantly White and historically Black colleges and universities. *Harvard Educational Review*, *62*(1), 26-44.

Alexander, F. K. (2000). The changing face of accountability: Monitoring and assessing institutional performance in higher education. *Journal of Higher Education*, 411-431.

Allison, P.D. (2002). *Missing data.* Thousand Oaks, CA: Sage.

Allison, P. D. (2009). *Fixed effects regression models*. Los Angeles: Sage.

Allison, P.D. (2010). Structural equation models class notes. Philadelphia, PA: Author.

Alon, S., & Tienda, M. (2005). Assessing the mismatch hypothesis: Differentials in college graduation rates by institutional selectivity. *Sociology of Education*, *78*(4), 294-315.

American Society of Engineering Education [ASEE]. (1974). Minorities in engineering: A blueprint for action. Washington, DC: ASEE, Planning Commission for Expanding Minority Opportunities in Engineering.

American Society for Engineering Education [ASEE]. (2010). *The green report: Engineering education for a changing world*. Retrieved from https://www.asee.org/papers-and-publications/publications/The-Green-Report.pdf.

American Society for Engineering Education. (2012). The organization. Retrieved from http://www.asee.org/about-us/the-organization.

Ami, C.G. (2001). *The effects of a four-week summer bridge program*. Alberquerque: University of New Mexico, Minority Engineering Program.

Anderson, E., & Kim, D. (2006). *Increasing the success of minority students in science and technology*. Washington, DC: American Council on Education.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies, 58*(2), 277-297.

Astin, A.W. (1975). Preventing students from dropping out. San Francisco, CA: Jossey-Bass.

Astin, A.W. (1984). Student involvement: A developmental theory for higher education. *Journal of College Student Personnel*, *25*, 297-308.

Astin, A. W. (1993). *What matters in college? Four critical years revisited*. San Francisco: Jossey-Bass.

Astin, A. W., & Astin, H. S. (1992). *Undergraduate science education: The impact of different college environments on the educational pipeline in the sciences.* Final Report. Los Angeles: Higher Education Research Institute.

Astin, A. W., & Oseguera, L. (2005). *Degree attainment rates at American colleges and universities* (Revised ed.). Los Angeles: Higher Education Research Institute, UCLA.

Augustine, N.A. (2011, January). Danger: America is losing its edge in innovation. *Forbes.com.* Retrieved from http://www.forbes.com/sites/ciocentral/2011/01/20/danger-america-is-losing-its-edge-in-innovation/

Baltagi, B.H. (2008). *Econometric analysis of panel data* (4th ed.). Chichester, UK: Wiley.

Barlow, A.E.L., Villarejo, M. (2004). Making a difference for minorities: Evaluation of and educational enrichment program. *Journal of Research in Science Teaching, 41*(9), 861-881.

Barron's Educational Series. (2012). *Barron's profiles of American colleges: Descriptions of the colleges*. Hauppauge, N.Y.: Barron's Educational Series, Inc.

Bauer, K.W., & Bennett, J.S. (2003). Alumni perceptions used to assess undergraduate research experience. *The Journal of Higher Education*, *74*(2), 210-230.

Bean, J. P. (1980). Dropouts and turnover: The synthesis and test of a causal model of student attrition. *Research in higher education*, *12*(2), 155-187.

Bean, J.P. (1981). *The synthesis of a theoretical model of student attrition*. Paper presented at the Annual Meeting of the American Educational Research Association (Los Angeles, CA, April 13-17, 1981).

Bennof, R.J. (2009). *Federal S&E obligations to three types of minority-serving institutions decline in FY 2007 (NSF-09319).* Arlington, VA: National Science Foundation.

Berger, J. B., & Braxton, J. M. (1998). Revising Tinto's interactionalist theory of student departure through theory elaboration: Examining the role of organizational attributes in the persistence process. *Research in Higher Education*, *39*(2), 103-119.

Berger, J. B., & Milem, J. F. (2000). Organizational behavior in higher education and student outcomes. In J. C. Smart (Ed.), *Higher education: Handbook of theory and research* (Vol. 15, pp. 268–338). New York: Agathon Press.

Bettinger, E., & Long, B.T. (2004). *Do college instructors matter? The effects of adjuncts and graduate assistants on students' interests and success* (Working Paper #10370). Washington, DC: National Bureau of Economic Research.

Bettinger, E. P., & Long, B. T. (2006). The increasing use of adjunct instructors at public institutions: Are we hurting students. In R. G. Ehrenberg (ed.), *What's happening to public higher education?* (pp. 51-69). Westport, CT: Praeger.

Blackwell, J. E. (1987). *Mainstreaming outsiders: The production of Black professionals*. Lanham, MD: Rowman & Littlefield.

Blose, G.L., Porter, J.D., & Kokkelenberg, E.C. (2006). The effect of institutional funding cuts on baccalaureate graduation rates in public higher education. In R. G. Ehrenberg (ed.), *What's happening to public higher education?* (pp. 71-82). Westport, CT: Praeger.

Bonous-Hammarth, M. (2000). Pathways to success: Affirming opportunities for science, mathematics, and engineering majors. *The Journal of Negro Education, 69*(1/2), 92-111.

Bonous-Hammarth, M. (2006). Promoting student participation in science, technology, engineering and mathematics careers. In W. R. Allen, M. Bonous-Hammarth, & R. T. Teranishi (Eds.), *Higher education in a global society: Achieving diversity, equity, and excellence* (pp. 269-282). Oxford, England: Elsevier.

Borrego, M. (2007a). Development of engineering education as a rigorous discipline: A study of the publication patterns of four coalitions. *Journal of Engineering Education, 96*(1), 5-18.

Borrego, M. (2007b). Conceptual difficulties experienced by trained engineers learning educational research methods. *Journal of Engineering Education, 96*(2), 91-102.

Bowen, W. G., & Bok, D. (1998). *The shape of the river*. Princeton, NJ: Princeton University Press.

Braxton, J.M., Hirschy, A.S., & McClendon, S.A. (2004). Understanding and reducing college student departure. *ASHE-ERIC Higher Education Report, 30*(3). San Francisco, CA: Jossey-Bass.

Brazziel, W. F., & Brazziel, M. E. (1997). *Distinctives of high producers of minority science and engineering doctoral starts.* Washington, DC: National Science Foundation.

Brown, A. R., Morning, C., and Watkins, C. B. (2005). Influence of African American engineering student perceptions of campus climate on graduation rates. *Journal of Engineering Education*, *94*(2), 263-271.

Burelli, J., & Rapoport, A. (2008). *Role of HBCUs as baccalaureate-origin institutions of Black S&E doctorate recipients.* (NSF-08-319). Arlington, VA: National Science Foundation.

Butz et al. (2004). *Is there a shortage of scientists and engineers? How would we know?* Santa Monica, CA: Rand Corporation.

Cabrera, A.F., Nora, A., & Castaneda, M.B. (1993). College persistence: Structured equation modeling test of an integrated model of student retention. *Journal of Higher Education, 64*(2), 123-139.

Cabrera, A.,F., Nora, A., Terenzini, P. T., Pascarella, E., & Hagedorn, L. S. (1999). Campus racial climate and the adjustment of students to college: A comparison between white students and African-American students. *Journal of Higher Education, 70*(2), 134-160.

Cameron, A.C., & Trivedi, P.K. (2010). *Microeconomics using Stata*. College Station, TX: Stata Press.

Carnavale, A.P., Smith, N., & Melton, M. (2010). *STEM*. Washington, DC: Georgetown University, Center on Education and the Workforce. Retrieved from http://www9.georgetown.edu/grad/gppi/hpi/cew/pdfs/stem-complete.pdf.

Carter, D. F. (2002). College students' degree aspirations: A theoretical model and literature review with a focus on African American and Latino students. In J. C. Smart (Ed.), *Higher education: A handbook of theory and research* (pp. 129-171). Bronx: Agathon Press.

Carter, F.D., Mandell, M., & Maton, K. (2009). The influence of on-campus, academic year undergraduate research on STEM Ph.D. outcomes: Evidence from the Meyerhoff Scholarship Program. *Educational Evaluation and Policy Analysis, 31*(4), 441-462.

Chang, M. J., Cerna, O., Han, J., and Sàenz, V. (2008). The contradictory roles of institution status in retaining underrepresented minorities in biomedical and behavioral science majors. *Review of Higher Education*, *31*(4), 433-464.

Chen, R. (2012). Institutional characteristics and college student dropout rates: A multilevel event history analysis. *Research in Higher Education, 53*(5), 487-505.

Chen, X. (2009). *Students who study science, technology, engineering, and mathematics (STEM) in postsecondary education (NCES 2009-161*). Washington, DC: National Center for Education Statistics.

Chubin, D. E., May, G. S., & Babco, E. L. (2005). Diversifying the engineering workforce. *Journal of Engineering Education*, *94*(1), 73-86.

Clewell, B.C., de Cohen, C.C., & Tsui, L. (2010). Capacity development to diversify STEM: Realizing the potential among HBCUs. Washington, DC: The Urban Institute.

Cole, D., & Espinoza, A. (2008). Examining the academic success of Latino students in science, technology, engineering, and mathematics (STEM) majors. *Journal of College Student Development*, *49*(4), 285-300.

Coleman, J.S., et. al. (1966). Equality of educational opportunities. Washington, DC: U.S. Office of Education.

Collins, L.M. (2006). Analysis of longitudinal data: The integration of theoretical model, temporal design, and statistical model. *Annual Review of Psychology, 57*, 505-528.

Committee on Equal Opportunities in Science and Engineering. (2004). *Broadening* *participation in America's science and engineering workforce.* Arlington, VA: National Science Foundation.

Cross, P., and Astin, H. (1981). Factors influencing Black students' persistence in college. In Thomas, G. (Ed.), *Black Students in Higher Education* (pp. 76-90). Greenwood Press, Westport, CT.

Culotta, E. (1992). Black colleges cultivate scientists. *Science, New Series, 258*(5085), 1216-1218.

Dale, S. B., & Krueger, A. B. (2002). Estimating the payoff to attending a more selective college: An application of selection on observables and unobservables. *The Quarterly Journal of Economics*, *117*(4), 1491-1527.

DeAngelo, L., Franke, R., Hurtado, S., Pryor, J. H., & Tran, S. (2011). *Completing college: Assessing graduation rates at four-year institutions*. Los Angeles: Higher Education Research Institute, UCLA.

Dolan, R.C., & Schmidt, R.M. (1994). Modeling institutional production of higher education. *Economics of Education Review, 13*(3), 197-213.

Dorans, N.J. (1999). Correspondences between ACT and SAT I scores. New York: The College Board.

Eagan, M. K., & Jaeger, A.J. (2008). Closing the gate: Part-time faculty instruction in gatekeeper courses and first-year persistence. *New Directions for Teaching and Learning, 115*, 39-53.

Eagan, M. K. (2010). *Moving beyond Frontiers: How institutional context affects degree production and student aspirations in stem*. (Doctoral dissertation). ProQuest LLC. 789 East Eisenhower Parkway, PO Box 1346, Ann Arbor, MI 48106.

Ehrenberg, R.G., & Rothstein, D.S. (1994). Do historically Black institutions of higher education confer unique advantages on Black students? An initial analysis. In R.G. Ehrenberg (Ed.), *Choices and consequences: Contemporary policy issues in education*. Ithaca, NY: ILR Press.

Ehrenberg, R. G., & Zhang, L. (2005). Do tenured and tenure-track faculty matter? *Journal of Human Resources, 40*(3), 647-659.

Elliott, R.A., Strenta, C., Adair, R., Matier, M., & and Scott, J. (1996). The role of ethnicity in choosing and leaving science in highly selective institutions. *Research in Higher Education*, 37(6), 681-709.

Engineering Trends. (2006). Unraveling the apparent inconsistencies between various sources of US engineering degree data - Comparison of ASEE, EWC and NSF surveys (Report 0806B). Retrieved from http://www.engtrends.com/IEE/0806B.php.

Engineering Workforce Commission. (2012). About EWC. Retrieved from http://ewc-online.org/about_ewc/ewc_history.asp

Evans, R. (1999). A comparison of success indicators for program and non-program participants in a community college summer bridge program for minority students. *Visions: The Journal of Applied Research for the Florida Association of Community Colleges, 2*(2), 6-14.

Felder, R.M., Mohr, P.H., Dietz, E.J., Baker-Ward, L. (1994). A longitudinal study of engineering student performance and retention, II: Difference between students from rural and urban backgrounds. *Journal of Engineering Education*, *83*(3), 209-217.

Felder, R.M., Felder, G.N., Mauney, M., Hamrin, C.E., Dietz, E.J. (1995). A longitudinal study of engineering student performance and retention, III: Gender differences in student performance and attitudes. *Journal of Engineering Education*, *84*(2), 151-163.

Felder, R.M., Felder, G.N., & Dietz, E.J. (2002). The effects of personality type on engineering student performance and attitudes. *Journal of Engineering Education, 91*(1), 3–17.

Fleming, J., & Morning, C. (1998). Correlates of the SAT in minority engineering students: An exploratory study. *The Journal of Higher Education, 69*, 89-108.

Flowers, L.A. (2004). Retaining African-American students in higher education: An integrative review. *Journal of College Student Retention, 6*(2), 23-35.

Fries-Britt, S. (1997). Identifying and supporting gifted African American men. *New Directions for Student Services,* (80), 65-78.

Fries-Britt, S. (1998). Moving beyond Black achiever isolation: Experiences of gifted Black collegians. *Journal of Higher Education, 69*(5), 556-576.

Fries-Britt, S.L., Younger, T.K., & Hall, W.D. (2010). Lessons from high-achieving students of color in physics. *New Directions for Institutional Research,* (148), 75-83.

Gansemer-Topf, A., & Schuh, J. H. (2006). Institutional selectivity and institutional expenditures: Examining organizational factors that contribute to retention and graduation. *Research in Higher Education, 47*(6), 613-642.

Garcia, E.P., & Stewart, J. (2012). Panel data analysis using Stata. College Station, TX: Stata Press.

Gasman, M., & Bowman, N. (2011). How to paint a better portrait of HBCUs. *Academe, 97*(3), 24-27.

Gasman, M., Lundy-Wagner, V., Ransom, T., & Bowman, N. (2010). Special issue: Unearthing promise and potential--our nations historically Black colleges and universities. *ASHE Higher Education Report*, *35*(5), 1-134.

Gelman, A., Hill, J., & Yajima, M. (2012). Why we (usually) don't have to worry about multiple comparisons. *Journal of Research on Educational Effectiveness, 5*, 189–211.

Georges, A. (1999). *Keeping what we've got: The impact of financial aid on minority retention in engineering.* New York: National Action Council for Minorities in Engineering.

Gibbons, M.T. (2010). *Engineering by the degrees*. Washington, DC: American Society for Engineering Education. Retrieved from http://www.asee.org/papers-and-publications/publications/college-profiles/2011-profile-engineering-statistics.pdf

Gloria, A. M., and Kurpius, S.E.R. (2001). Influences of self-beliefs, social support, and comfort in the university environment on the academic nonpersistence decisions of American Indian undergraduates. *Cultural Diversity and Ethnic Minority Psychology, 7*(1), 88–102.

Goenner, C. F., & Snaith, S. M. (2004). Accounting for model uncertainty in the prediction of university graduation rates. *Research in Higher Education, 45*(1), 25-41.

Good, J., Halpin, G, & Halpin, G. (2000). A promising prospect for minority retention: Students becoming peer mentors. *The Journal of Negro Education, 69*(4), 375-383.

Good, J., Halpin, G, & Halpin, G. (2002). Retaining Black students in engineering: Do minority programs have a longitudinal impact? *Journal of College Student Retention, 3*, 351-364.

Grandy, J. (1998). Persistence in science of high-ability minority students. *Journal of Higher Education, 69*(6), 589–620.

Greene, W. H. (2007). The econometric approach to efficiency analysis. In H. O. Fried, C. A. K. Lovell and S. S. Schmidt (Eds.). *The measurement of productive efficiency: Techniques and applications.* New York: Oxford University Press.

Griffin, K.A., Perez, D., Holmes, A.P., & Mayo, C.E. (2010). Investing in the future: The importance of faculty mentoring in the development of student of color in STEM. *New Directions for Institutional Research, 148*(2010), 95-103.

Griffith, A. L. (2010). Persistence of women and minorities in STEM field majors: Is it the school that matters?. *Economics of Education Review*, *29*(6), 911-922.

Guiffrida, D.A. (2006). Toward a cultural advancement of Tinto's theory. *The Review of Higher Education*, *29*(4), 451-472.

Hackett, G., Betz, N. E., Casas, J., and Rocha-Singh, I. A. (1992). Gender, ethnicity, and social cognitive factors predicting the academic achievement of students in engineering. *Journal of Counseling Psychology*, *3*(4), 527–538.

Hamrick, F. A., Schuh, J. H., & Shelley, M. C. (2004). Predicting higher education graduation rates from institutional characteristics and resource allocation. *Education Policy Analysis Archives*, *12*, 24.

Hanushek, E.A. (1979). Conceptual and empirical issues in the estimation of educational production functions. *The Journal of Human Resources*, *14*(3), 351-388.

Harper, S. R., and Hurtado, S. (2007). Nine themes in campus racial climates. In S. R. Harper and L. D. Patton (Eds.), *Responding to the realities of race on campus. New directions for student services* (pp. 7–24). San Francisco: Jossey-Bass.

Harris, D. (2010). Education production functions: Concepts. In Brewer, D. J. & McEwan, P. J. (Eds.) *Economics of education* (pp.127-131). Amsterdam: Elsevier.

Hartwig, W.H. (1978). An historical analysis of engineering college research and degree programs as dynamic systems. *Proceedings of the IEEE*, *66*(8), 829-837.

Henderson, C., Finkelstein, N., & Beach, A. (2010). Beyond dissemination in college science teaching: An introduction to four core change strategies. *Journal of College Science Teaching*, *39*(5), 18-25.

Higher Education Research Institute. (2010). Degrees of success: *Bachelor's degree completion rates among initial STEM majors*. Los Angeles: Higher Education Research Institute.

Hopkins, D.S. (1990). The higher education production function: Theoretical foundations and empirical findings. In S. Hoenack & E. Collins (Eds.), *The Economics of American Universities: Management Operations, and Fiscal Environment*, State University of New York Press: Albany, NY.

Hrabowski, F.A.(2002). Raising minority achievement in science and math. *Educational Leadership, 60*(4), 44-48.

Hrabowski, FA., & Maton, K.I. (1995). Enhancing the success of African-American students in the sciences: Freshman year outcomes. *School Science and Mathematics, 95*(1), 19-27.

Hrabowski, F. A., and Maton, K. I. (2009). Change institutional culture, and you change who goes into science. *Academic, 95*(3), 11–16.

Hsiao, C. (2007). Panel data analysis—advantages and challenges. *Test*,*16*(1), 1-22.

Huang, G., Taddese, N., & Walter, E. (2000). *Entry and persistence of Women and Minorities in college science and engineering education*. Washington, DC: U.S. Department of Education, National Center for Education Statistics.

Hubbard, S.M., & Stage, F.K. (2010). Identifying comprehensive public institutions that develop minority scientists. *New Directions for Institutional Research*, (148), 53-62.

Hurtado, S., & Carter, D.F. (1996). Latino students' sense of belonging in the college community: Rethinking the concept of integration on campus. In *College students: The evolving nature of research*. Needham Heights, MA: Simon & Schuster.

Hurtado, S., Cabrera, N.L., Lin, M.H., Arellano, L., & Espinosa, L.L. (2009). Diversifying science: Underrepresented student experiences in structured research programs. *Research in Higher Education, 50*(2), 189– 214.

Hurtado, S., Eagan, M.K., Cabrera, N.L., Lin, M.H., Park, J., Lopez, M. (2008). Training future scientists: Predicting first-year minority student participation in health science research. *Research in Higher Education, 49*(2), 126–152.

Hurtado, S., Han, J.C., Saenz, V., Espinosa, L.L., Cabrera, N.L., & Cerna, O. (2007). Predicting transition and adjustment to college: Biomedical and behavioral science aspirants' and minority students' first year of college. *Research in Higher Education, 48*(7), 481–887.

Hurtado, S., Newman, C.B., Tran, M.C., & Chang, M.J. (2010). Improving the rate of success for underrepresented racial minorities in STEM fields: Insights from a national project. *New Directions for Institutional Research*, (148), 5-15.

Hurtado, S., Eagan, M. K., & Hughes, B. (2012). *Priming the pump or the sieve: institutional contexts and URM STEM degree attainments*. Paper presented at the Annual Forum of the Association for Institutional Research Association, New Orleans, LA.

Ibarra, R.A. (1999). Multicontextuality: A new perspective on minority underrepresentation in SEM academic fields. *Making Strides (American Association for the Advancement of Science), 1*(3), 1-9.

Identified. (2011). *Revenge of the nerds: Engineers have never had it better*. Retrieved from http://identified.typepad.com/wp/revengeofthenerdspart1.pdf.

Jackson, L.A., Gardner, P.D., & Sullivan, L.A. (1993). Engineering persistence: Past, present, and future factors and gender differences. *Higher Education*, *26*(2), 227-246.

Johnson, A. (2007). Unintended consequences: How science professors discourage women of color. *Science Education, 91*, 805-821.

Jones, L.S. (1998). The myth of meritocracy and delusions of equity: Cultural impediments to diversity in natural science programs. Paper presented at the annual meeting of the American Educational Research Association, San Diego, CA.

Jones, M.T., Barlow, A.E.L., Villarejo, M. (2010). Importance of undergraduate research for minority persistence and achievement in biology. *The Journal of Higher Education, 81*(1), 82-115.

Kane, T. J. (1994). *Race, college attendance and college completion.* Washington, DC: U.S. Department of Education.

Kansas Board of Reagents. (2011, March 25). Reagents applaud senate's approval of state engineering initiative. Retrieved from http://www.kansasregents.org/regents_applaud_senate_s_approval_of_engineering_initiative.

Kardash, C.M. (2000). Evaluation of and undergraduate research experience: Perceptions of undergraduate interns and their faculty mentors. *Journal of Educational Psychology, 92*(1), 191-201.

Kelly, P.J. (2009). *The dreaded "P" word: An examination of productivity in public postsecondary education*. Washington, DC: Delta Cost Project.

Kiley, K. (2011, September 16). Where universities can be cut. *Inside Higher Ed Online.* Retrieved from http://www.insidehighered.com/news/2011/09/16/unc_berkeley_cornell_experience_show_where_administrative_cuts_can_be_made.

Kim, M.M. (2002). Historically black vs. white institutions: Academic development among black students. *Review of Higher Education , 25*(4) 385-407.

Kim, M. M., & Conrad, C. F. (2006). The impact of historically black colleges and universities on the academic success of African-American students. *Research in Higher Education*, *47*(4), 399-427.

Kim, M. M., Rhoades, G., & Woodard Jr, D. B. (2003). Sponsored research versus graduating students? Intervening variables and unanticipated findings in public research universities. *Research in higher education*, *44*(1), 51-81.

Kuh, G.D., Kinzie, J., Buckley, J.A., Bridges, B.K., & Hayek, J.C. (2006). *What matters to student success: A review of the literature.* Washington, DC: National Postsecondary Education Cooperative.

Kuh, G.D., & Love, P.G. (2000). A cultural perspective on student departure. In J.M. Braxton (Ed.), *Reworking the student departure puzzle*, 196-212. Nashville, TN: Vanderbilt University Press.

Kumbhakar, S. C., & Lovell, C. K. (2000). *Stochastic frontier analysis*. Cambridge University Press.

Landis, R.B. (1988). The case for minority engineering programs. *Engineering Education*, *78*, 756-761.

Laursen, S., Hunter, A., Seymour, E., Thiry, H., & Melton, G. (2010). *Undergraduate research in the sciences: Engaging students in real science*. San Francisco, CA: Jossey-Bass.

Leetaru, K. (2010). A new look at the institutional impact on women in postsecondary engineering education 1966-2007. *Journal of Women and Minorities in Science and Engineering*, 16 (2), 177–197.

Leggon, C. B. (2010). Diversifying science and engineering faculties: Intersections of race, ethnicity, and gender. *American Behavioral Scientist*,*53*(7), 1013-1028.

Leggon, C. B., & Pearson, W. (1997). The baccalaureate origins of African American female Ph.D. scientists. *Journal of Women and Minorities in Science and Engineering*, *3*(4), 213-224.

Lenihan, C. (2012). IPEDS *Analytics: Delta Cost Project Database 1987-2010* (NCES 2012-823). Washington, DC: National Center for Education Statistics. Retrieved from http://nces.ed.gov/pubs2012/2012823.pdf.

Lent et al. (2005). Social cognitive predictors of academic interests and goals in engineering: Utility for women and students at historically Black universities. *Journal of Counseling Psychology, 52*(1), 84-92.

Lent, R. W., Sheu, H.B., Singley, D., Schmidt, J. A., Schmidt, L. C., & Gloster, C. S. (2008). Longitudinal relations of self-efficacy to outcome expectations, interests, and major choice goals in engineering students. *Journal of Vocational Behavior, 73*, 328–35.

Leslie, L. L., McClure, G. T., and Oaxaca, R. L. (1998). Women and minorities in science and engineering: A life sequence analysis. *Journal of Higher Education, 69*(3), 239–276.

Lewis, D.R., & Dundar, H. (2001). Costs and productivity in higher education: Theory, evidence, and policy implication. In Paulsen, M. B., & Smart, J. C. (Eds.) *The finance of higher education: Theory, research, policy, and practice* (pp. 133-188). New York: Agathon Press.

Li, X., & Carroll, C. D. (2007). *Characteristics of minority-serving institutions and minority undergraduates enrolled in these institutions: Postsecondary education descriptive analysis report (NCES 2008-156).* Washington, DC: National Center for Education Statistics.

Lopatto, D. (2004). Survey of Undergraduate Research Experience (SURE): First findings. *Cell Biology Education, 3*, 270-277.

Lopatto, D. (2007). Undergraduate research experiences support science career decisions and active learning. *CBE – Life Sciences Education, 6*, 297-306.

Lusterman, S. (1979). *Minorities in engineering: The corporate role (no. 756)*. New York: The Conference Board.

Malcom, L.E. (2008). Accumulating (dis)advantage: Institutional and financial aid pathways of Latino STEM baccalaureates. Unpublished doctoral dissertation, University of Southern California.

Malcom, L.E. (2010). Charting the pathways to STEM for Latino/a students: The role of community colleges. New Directions for Institutional Research, 148, 29-40.

Malone, K.R, & Barabino, G. (2009). Narrations of race in STEM research settings:

Identity formation and its discontents. *Science Education, 93*(3), 485-510.

Matthews, C.M. (2011). *Federal Research and Development Funding at Historically Black Colleges and Universities*. Washington, DC: Congressional Research Service.

Maton, K.I., & Hrabowski, F.A. (2004). Increasing the number of African American PhDs in the sciences and engineering: A strengths-based approach. *American Psychologist, 59*(6), 547-556.

Maton, K.I., Hrabowski,F.A., & Schmitt, C.L. (2000). African American college students excelling in the sciences: College and postcollege outcomes in the Meyerhoff Scholars Program. *Journal of Research in Science Teaching, 37*(7), 629-654.

May, G.S., & Chubin, D.E. (2003). A retrospective on undergraduate engineering success for underrepresented minority students. *Journal of Engineering Education, 92*(1), 27-39.

Mervis, J. (2001). Student research: What is it good for? *Science, 293*, 1614-1615.

Metz, G.W. (2004). Challenge and changes to Tinto's persistence theory: A historical review. *Journal of College Student Retention, 6*(7), 191-207.

Middaugh, M.F., Graham, R., & Shahid, A. (2003). *A study of higher education instructional expenditures: The Delaware study of instructional costs and productivity*. *NCES 2003-161*. Washington, DC: U.S. Department of Education, National Center for Education Statistics. ,

Mokyr, J. (2002). Innovation in an historical perspective: Tales of technology and evolution. In B. Steil, D. G. Victor, & R. R. Nelson (Eds.), *Technological Innovation and Economic Performance*. Princeton, NJ: Princeton University Press.

Moore , J. L. (2006). A qualitative investigation of African American males' career trajectory in engineering: Implications for teachers, school counselors, and parents. *The Teachers College Record*, *108*(2), 246-266.

Moore, J. L., Madison-Colmore, O., & Smith, D. M. (2003). The prove-them-wrong syndrome: Voices from unheard African-American males in engineering disciplines. *The Journal of Men's Studies, 12*(1), 61-73.

Morrison, M. C. (2012). Graduation odds and probabilities among baccalaureate colleges and universities. *Journal of College Student Retention: Research, Theory and Practice*, *14*(2), 157-179.

Morrow, R. (1994). Issues facing engineering education. *Journal of Engineering Education, 83*(1), 15-18.

Morse, L.C., & Babcock, D.L. (2009). Managing engineering and technology: An introduction to management for engineers. Upper Saddle River, NJ: Prentice Hall.

Multiple-Institution Database for Investigating Engineering Longitudinal Development [MIDFIELD]. (2013). *Project summary*. Retrieved from https://engineering.purdue.edu/MIDFIELD/Summary.htm.

Museus, S.D., & Liverman, D. (2010). High-performing institutions and their implications for studying underrepresented minority students in STEM. *New Directions for Institutional Research*, (148), 5-15.

Museus, S. D., Palmer, R.,T., Davis, R. J., & Maramba, D. C. (2011). Special issue: Racial and ethnic minority students success in STEM education. *ASHE Higher Education Report, 36*(6), 1-140.

Nagda, B.A., Gregerman, S.R., Jonides, J., von Hippel, W., & Lerner, J.S. (1998). Undergraduate student-faculty research partnerships affect student retention. *The Review of Higher Education, 22*(1), 55-72.

National Academy of Engineering. (2008). *Grand challenges for engineering.* Washington, DC: National Academies Press.

National Academy of Engineering. (2003). *A century of innovation: Twenty engineering achievements that transformed our lives*. Washington DC: National Academies Press.

National Academy of Sciences. (2007). *Rising above the gathering storm: Energizing and employing America for a brighter economic future*. Washington, DC: National Academies Press.

National Academy of Sciences. (2010). *Rising above the gathering storm, revisited: Rapidly approaching category 5*. Washington, DC: National Academies Press.

National Academy of Sciences. (2011*). Expanding underrepresented minority participation: America's science and technology talent at the crossroads.* Washington, DC: National Academies Press.

National Action Council for Minorities in Engineering. (2012). African Americans in engineering. *NACME Research Briefs, 2*(4), 1-2.

National Action Council for Minorities in Engineering. (2011). African Americans in engineering. *NACME Research Briefs*, *1*(4), 1-2.

National Center for Science and Engineering Statistics [NCSES]. 2013. Higher Education Research and Development Survey. Retrieved from http://www.nsf.gov/statistics/srvyherd/.

National Economic Council, Council of Economic Advisers, & Office of Science and Technology Policy. (2011). A strategy for American innovation: Securing our economic growth and prosperity. Washington, DC: Authors. Retrieved from http://www.whitehouse.gov/sites/default/files/uploads/InnovationStrategy.pdf.

National Science Board. (1986). *Undergraduate science, mathematics, and engineering education (NSB-86-100)*. Washington, DC: National Science Foundation.

National Science Board. (2008). *Science and engineering indicators 2008* (NSB 08-01) Arlington, VA: National Science Foundation.

National Science Board. (2010). *Science and engineering indicators 2010 (NSB 10-01).* Arlington, VA: National Science Foundation.

National Science Board. (2012). *Science and Engineering Indicators 2012 (NSB 12-01).* Arlington, VA: National Science Foundation.

National Science Foundation. (1982). *Women and Minorities in Science and Engineering: 1982*. *(NSF 82-302*). Washington, DC: National Science Foundation.

National Science Foundation. (2008). *The Division of Engineering Education and Centers division plan, 2007-2011*. Arlington, VA: National Science Foundation.

National Science Foundation. (2011a). *Science and engineering degrees: 1966–2008.* Arlington, VA: National Center for Science and Engineering Statistics. Retrieved from http://www.nsf.gov/statistics/nsf11316/.

National Science Foundation. (2011b). *Women, Minorities, and Persons with Disabilities in Science and Engineering: 2011*. Special Report NSF 11-309. Arlington, VA: National Science Foundation, Division of Science Resources Statistics. Retrieved from http://www.nsf.gov/statistics/wmpd/.

Nelson, D.J., & Rogers, D.C. (2007). A national analysis of diversity in science and engineering faculties at research universities. Norman: University of Oklahoma, Department of Chemistry.

Nelson, R.R. (Ed.). (1993). *National innovation systems: A comparative analysis.* New York: Oxford University Press.

Newman, C.B. (2011a). Access and success for African American engineers and computer scientists: A case study of two predominantly White Public Research Universities. (Unpublished doctoral dissertation). University of California, Los Angeles.

Newman, C. B. (2011b). Engineering success: The role of faculty relationships with African American undergraduates. *Journal of Women and Minorities in Science and Engineering*, *17*(3), 193-209.

Nora, A. (2001). The depiction of significant others in Tinto's "Rites of Passage": A reconceptualization of the influence of family and community in the persistence process. *Journal of College Student Retention: Research Theory and Practice, 3,* 41-40.

Ohland, M.W., Sheppard, S.D., Lichtenstein, G., Eris, O., Chachra, D., & Layton, R.A. (2008). Persistence, engagement, and migration in engineering programs. *Journal of Engineering Education, 97*(3), 259-278.

Ohland, M.W., & Zhang, G. (2002). A study of the impact of minority engineering programs at the FAMU-FSU College of Engineering. *Journal of Engineering Education, 91*(4), 435-440.

Ong, M., Wright, C., Espinosa, L.L., & Orfield, G. (2011). Inside the double blind: A synthesis of empirical research on undergraduate and graduate women of color in science, technology, engineering, and mathematics. *Harvard Education Review*, 81 (2), 172-390.

Oseguera, L., Hurtado, S., Denson, N., Cerna, O., Saenz, V. (2006). The characteristics and experiences of minority freshmen committed to biomedical and behavioral science research careers." *Journal of Women and Minorities in Science and Engineering,* 2006, *12*(2–3), 155–177.

Oseguera, L., & Rhee, B. S. (2009). The influence of institutional retention climates on student persistence to degree completion: A multilevel approach. *Research in Higher Education, 50*(6), 546-569.

Ostreko, A. (2012). *The institutional degree production of master's and doctorates for women and underrepresented minorities in engineering*. (Unpublished doctoral dissertation). University of Kansas, Lawrence, KS.

Pascarella, E. T., Smart, J. C., Ethington, C. A., & Nettles, M. T. (1987). The influence of college on self-concept: A consideration of race and gender differences. *American Educational Research Journal, 24*(1), 49-77.

Pascarella, E., & Terenzini, P. (1991). *How college affects students.* San Francisco, CA: Jossey-Bass.

Pascarella, E.T., & Terenzini, P.T. (2005). *How college affects students: A third decade of research. Volume 2.* San Francisco, CA: Jossey-Bass.

Paulsen, M. B., & Toutkoushian, R. K. (2006). Overview of economic concepts, models, and methods for institutional research. *New Directions for Institutional Research*, (132), 5-24.

Pearson, W., Jr, & Pearson, L. C. (1985). Baccalaureate origins of Black American scientists: A cohort analysis. *Journal of Negro Education, 54*(1), 24-34.

Perna, L. W. (2003). *The key to college access: A rigorous college preparatory curriculum*. Paper presented at the annual meeting of the American Educational Research Association, Chicago, IL.

Perna, L.W., Lundy-Wagner, V.C., Drezner, N.D., Gasman, M., Yoon, S., Bose, E., & Gary, S. (2009). The contribution of HBCUs to the preparation of African American women for STEM careers: A case study. *Research in Higher Education, 50*(1), 1-23.

Perna L.W., & Thomas, S.L. (2006). *A framework or reducing the college success gap and promoting success for all.* Washington, DC: National Postsecondary Educational Cooperative.

Peerenboom, J. (2012). *Exploring links among institutional expenditure patterns, undergraduate graduation rates, and time-to-degree at public, four-year colleges and universities*. (Unpublished doctoral dissertation). Florida State University, Tallahassee, FL.

Petroski, H. (2010). *The essential engineer.* New York: Random House.

Pike, G. R., Smart, J. C., Kuh, G. D., & Hayek, J. C. (2006). Educational expenditures and student engagement: When does money matter?. *Research in Higher Education, 47*(7), 847-872.

Price, J. (2010). The effect of instructor race and gender on student persistence in STEM fields. *Economics of Education Review, 29*(2010), 901-910.

Price, J. L. (1977). *The study of turnover*. Ames: Iowa State University Press.

Reichert, M., & Absher, M. (1997). Taking another look at educating African American engineers: The importance of undergraduate retention. *Journal of Engineering Education, 86*(3), 241–253.

Roper, C. (2011). *Developing talent in science and technology: Institutional factors and minorities in the STEM disciplines.* Clemson, SC: Clemson University, Charles H. Houston Center for the Study of the Black Experience in Education.

Rosenbaum, P. R. (2005). Observational study. *Encyclopedia of statistics in behavioral science*.

Rubin, D.B. (1987) *Multiple imputation for nonresponse in surveys*. New York: J. Wiley & Sons.

Ryan, J.F. (2004). The relationship between institutional expenditures and degree attainment at baccalaureate colleges. Research in higher education, 45(2), 97-114.

Santiago, A.M., & Einarson, M.K. (1998). Background characteristics as predictors of academic self-confidence and academic self-efficacy among graduate science and engineering students. *Research in Higher Education, 39*(2), 163-198.

Salerno, C.S. (2002). On the technical and allocative efficiency of research-intensive higher education institutions. (Unpublished doctoral dissertation). Pennsylvania State University, State College, PA.

Salerno, C.S. (2003). *What we know about the efficiency of higher education institutions: The best evidence*. Enschede, Netherlands: University of Twente, Center for Higher Education Policy Studies.

Schibik, T., & Harrington, C. (2004). Caveat emptor: Is there a relationship between part-time faculty utilization and student learning outcomes and retention? *AIR Professional File*, (91), 1-10.

Schochet, P.Z. (2008). *Technical methods report: Guidelines for multiple testing in impact evaluations* (NCEE 2008-4018). Washington, DC: U.S. Department of Education, National Center for Education Evaluation and Regional Assistance.

Scott, M., Bailey, T., & Kienzl, G. (2006). Relative success? Determinants of college graduation rates in public and private colleges in the U.S. *Research in Higher Education 47*(3), 249-279.

Seymour, E., & Hewitt, N.M. (1997). *Talking about leaving: Why undergraduates leave* *the sciences.* Boulder, CO: Westview Press.

Shelton, R.D. & Prabhakar, J.C. (1971). Efficiency ratios for engineering schools. *Proceedings of the IEEE*, 59 (6), 843-848.

Sibulkin, A. E., & Butler, J. S. (2005). Differences in graduation rates between young Black and White college students: Effect of entry into parenthood and historically Black universities. *Research in Higher Education, 46*(3), 327-348.

Sibulkin, A. E., & Butler, J. S. (2011). Diverse colleges of origin of African American doctoral recipients, 2001-2005: Historically Black colleges and universities and beyond. *Research in Higher Education, 52*(8), 830-852.

Slaughter, J. B. (2009). African American males in engineering: Past, present, and future of opportunity. *Diversity in Higher Education*, *7*, 193-208.

Smyth, F. L., and McArdle, J. J. (2004). Ethnic and gender differences in science graduation at selective colleges with implications for admission policy and college choice. *Research in Higher Education, 45,* 353–381.

Solórzano, D. G. (1995). The doctorate production and baccalaureate origins of African Americans in the sciences and engineering. *Journal of Negro Education, 64*(1), 15-32.

Solow, R.M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics, 39*(3), 312-320.

Solow, R.M. (1987). Nobel Prize award ceremony speech. Retrieved from http://www.nobelprize.org/nobel_prizes/economics/laureates/1987/presentation-speech.html.

Southern Education Foundation (2005). *Igniting potential: Historically black colleges and universities in science, technology, engineering and mathematics*. Atlanta, GA: Author.

Stanford News Service. (1995, June 7). Too much efficiency not good for higher education, March argues. Retrieved from http://news.stanford.edu/pr/95/950607Arc5193.html.

StataCorp. (2011). *Stata 12 Reference Manual*. College Station, TX: Stata Press.

Suitts, S. (2003). Fueling education reform: Historically Black colleges are meeting a national science imperative. *Cell Biology Education, 2*, 205–206.

Summers, M., & Hrabowski, F. 2006. Preparing minority scientists and engineers.

Science, 311(5769), 1870-1871.

Suresh, R. (2006). The relationship between barrier courses and persistence in engineering. *Journal of College Student Development, 8*(2), 215-239.

Swail, W.S., Redd, K.E., & Perna, L.W. (2003). Retaining minority students in higher education: A framework for success. *ASHE-ERIC Higher Education Report, 30(2).*

Tapia, R.A. (2009, March 27). Minority students and research universities: How to overcome the "mismatch." *Chronicle of Higher Education, 55*(29), 72.

Terenzini, P., Rendon, L., Upcraft, M.L., Millar, S., Allison, K., Gregg, P., & Jalomo, R. (1994). The transition to college: Diverse students, diverse stories. *Research in Higher Education, 35*, 57-73.

Thelin, J.R. (2004). *A history of American higher education* (1st Edition). Baltimore, MD: Johns Hopkins Press.

Thiry, H., & Laursen, S.L. (2011). The role of student-advisor interactions in apprenticing undergraduate researchers into a scientific community of practice. *Education and Technology, 20*(6), 771-784.

Thomas, G.E. (1987). African -American college students and their major field choice. In A.S. Pruitt (Ed.), *In pursuit of equality in higher education* (pp. 105-115). Dix Hills, NY: General Hall.

Thomas, G.E. (1991). Assessing the college major selection process for African-American students. W.R. Allen, E. Epps, & N. Hanniff (Eds.), *College in Black and White: African American students in predominantly White and historically Black universities*. Albany: State University of New York Press.

Tierney, W.G. (1999). Models of minority college-going and retention: Cultural integrity versus cultural suicide. *Journal of Negro Education, 68*(1), 80-91.

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research, 45*, 89-125.

Tinto, V. (1987). *Leaving college: Rethinking the causes and cures of student attrition.* Chicago: University of Chicago Press.

Tinto, V. (1993). *Leaving college: Rethinking the causes and cures of student attrition* (2nd ed.). Chicago: University of Chicago Press.

Tinto, V. (2006). Research and practice of student retention: What next? *Journal of*

College student Retention, 8(1), 1-19.

Tinto, V., & Pusser, B. (2006). *Moving from theory to action: Building a model of institutional action for student success*. Washington, DC, National Postsecondary Education Cooperative.

Titus, M. A. (2004). An examination of the influence of institutional context on student persistence at 4-year colleges and universities: A multilevel approach. *Research in Higher Education, 45*(7), 673-699.

Titus, M. A. (2006a). Understanding college degree completion of students with low socioeconomic status: The influence of the institutional financial context. *Research in Higher Education, 47*(4), 371-398.

Titus, M. A. (2006b). Understanding the influence of the financial context of institutions on student persistence at four-year colleges and universities. *Journal of Higher Education, 77*(2), 353-375.

Titus, M.A., & Eagan, M.K. (2008). Degree productivity and cost efficiency in U.S. public four-year colleges and universities: Is there a trade off? Paper presented at the 2008 Annual Forum of the American for Institutional Research, Seattle, WA.

Titus, M. A. (2009). The production of bachelor's degrees and financial aspects of state higher education policy: A dynamic analysis. *Journal of Higher Education, 80*(4), 439-468.

Torres, V. (2003). Influence on ethnic identity development of Latino students in the first two years of college. *Journal of College Student Development, 44*, 532-547.

Toutkoushian, R.K. (2001). Trends in revenues and expenditures for public and private higher education. In Paulsen, M. B., & Smart, J. C. (Eds.) *The finance of higher education: Theory, research, policy, and practice* (pp. 11-38). New York: Agathon Press.

Toutkoushian, R. K., & Smart, J. C. (2001). Do institutional characteristics affect student gains from college? *The Review of Higher Education, 25*, 39-61.

Treisman, P. (1985). A model academic support system, in R. Landis (Ed.), *Handbook on improving retention and graduation of minorities in engineering*. New York: National Action Council for Minorities in Engineering.

Trent, W.T. (1991). *Focus on equity: Race and gender differences in degree attainment, 1975-76, 1980-81*. In W.R. Allen, E. Epps, & N. Hanniff (Eds.), *College in Black and White: African American students in predominantly White and historically Black universities*. Albany: State University of New York Press.

Trent, W.T., & Hill, J. (1994). The contributions of historically Black colleges and university to the production of African American scientist and engineers. In W. Pearson & A. Fetcher (Eds.), *Who will do science? Educating the next generation*. Baltimore, Md: John Hopkins University Press.

Tsiu, L. (2007). Effective strategies to increase diversity in STEM fields: A review of the literature. *Journal of Negro Education, 76*(4), 555-581.

University of Maryland. (2012). *The Meyerhoff Scholars Program*. Retrieved from http://www.umbc.edu/meyerhoff/.

The Urban Institute. (2005). *Final report on the evaluation of the National Science Foundation Louis Stokes Alliances for Minority Participation Program*. Washington, DC: The Urban Institute, Program for Evaluation and Equity Research.

U.S. Commission on Civil Rights. (2010). Encouraging minority students to pursue science, technology, engineering, and math careers. Washington, DC: Author.

U.S. Department of Commerce. (2012). The competitiveness and innovative capacity of the United States. Washington, DC: U.S. Department of Commerce. Retrieved from http://www.commerce.gov/sites/default/files/documents/2012/january/competes_010511_0.pdf.

U.S. Department of Commerce. (2013). National income and product accounts tables. Retrieved from http://www.bea.gov/iTable/iTable.cfm?ReqID=9&step=1#reqid=9&step=1&isuri=1.

U.S. Department of Education. (2007). *Report of the Academic Competitiveness Council.* Washington, DC: U.S. Department of Education.

U.S. Department of Education. (2012). IPEDS finance data FASB GASB – What's the difference? Retrieved from http://nces.ed.gov/ipeds/factsheets/fct_ipeds_finance_03072007_1.asp.

U.S. Department of Education. (2013). IPEDS glossary. Retrieved from http://nces.ed.gov/ipeds/glossary/index.asp?id=854.

Walpole, M., Simmerman, H., Mack, C., Mills, J.T., Scales, M., & Albano, D. (2008). Bridge to success: Insight into summer bridge program students' college transition. *Journal of The First-Year Experience & Students in Transition, 20*(1), 11-30.

Watson, K., & Froyd, J. (2007). Diversifying the U.S. engineering workforce: A new model. *Journal of Engineering Education*, *96*(1), 19–32.

Webber, D. A., & Ehrenberg, R. G. (2010). Do expenditures other than instructional expenditures affect graduation and persistence rates in american higher education? *Economics of Education Review, 29*(6), 947-958.

Webber, D. A. (2012). Expenditures and postsecondary graduation: An investigation using individual-level data from the state of Ohio. *Economics of Education Review, 31*(5), 615-618.

Weinberger, C. (2011). *Engineering educational opportunity: Impacts of 1980s policies to increase the share of black college graduates with a major in engineering or computer science*.

Wellman, J.V. (2010). *Connecting the dots between learning and resources.* Champaign: National Institute for Learning Outcomes Assessment (NILOA), University of Illinois at Urbana-Champaign.

Wenglinsky, H. (1997). *Students at historically Black colleges and universities: Their aspirations & accomplishments.* Princeton, NJ: Educational Testing Service, Policy Information Center.

Wilburn, A. Y. (1974). Careers in science and engineering for Black Americans. *Science*, *184*(4142), 1148-1154.

Willemsen, E. W. (1995). So what is the problem? Difficulties at the gate. *New directions for teaching and learning, 61*, 55-22.

Wolf-Wendel, L. (1998). Models of excellence: The baccalaureate origins of successful European American women, African American women, and Latinas. *Journal of Higher Education, 69*(2), 141-186.

Wolf-Wendel, L., Baker, B. D., & Morphew, C. C. (2000). Dollars and $ense: Institutional resources and the baccalaureate origins of women doctorates. *Journal of Higher Education*, *71*(2), 165-186.

Wooldridge, J. M. (2009). *Introductory econometrics: a modern approach*. Mason, OH: South-Western.

Yoder, B.L. (2012). Engineering by the degrees. Washington, DC: American Society for Engineering Education. Retrieved from http://www.asee.org/papers-and-publications/publications/college-profiles/2011-profile-engineering-statistics.pdf.

Zhang, G., Anderson, T.J., Ohland, M.W., Carter, R., & Thorndyke, B. (2004). Identifying factors influencing engineering student graduation and retention: A longitudinal and cross-institutional study. *Journal of Engineering Education*, 93(4).

Zhang, L. (2007). Nonresident enrollment demand in public higher education: An analysis at national, state, and institutional levels. *Review of Higher Education, 31*(1), 1-25.

Zhang, L. (2009). Does state funding affect graduation rates at public four-year colleges and universities? *Educational Policy*,*23*(5), 714-731.

Zhang, L. (2010). The use of panel data methods in higher education policy studies. In John Smart (Ed.) *Higher Education: Handbook of Theory and Research, vol. 25* (pp. 309-347). The Netherlands: Springer.

Zhang, L. (2011). Does merit-based aid affect degree production in STEM fields? evidence from Georgia and Florida. *Journal of Higher Education, 82*(4), 389-415.

Zhe, J., Doverspike, D., Zhao, J., Lam, P., Menzemer, C. (2010). High school bridge program: A multidisciplinary research program. *Journal of STEM Education, 11*(1), 61-68.

Zydney, A.L., Bennett, J.S., Shahid, A., & Bauer, K.W. (2002). Impact of undergraduate research experience in engineering. Journal of Engineering Education . *Journal of Engineering Education, 91*, 151–157.