What Does it Mean to “Have the Means”?: Increasing Historically Marginalized Students’ Access to Capital and Academic Success

By

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In memory of my grandfather, Dr. Vasant Kelkar,

who understood the world through science and stories.

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Chapter 1

Introduction

Students from historically marginalized populations, such as English Learners, first-generation students, or students from low-income backgrounds, face numerous roadblocks accessing educational opportunities. These barriers often stem from gaps in access to key forms of capital—including human, financial, cultural, and social capital (Barry et al., 2009; Bui, 2002; Inman & Mayes, 1999; Johnson, 2008; Martinez et al., 2009; Pascarella et al., 2004; Schwartz et al., 2017; Terenzini et al., 1996; Tobolowsky et al., 2017). High levels of these forms of capital creates opportunities for students to access expertise, information, tools, and resources to support their academic development. To the extent that institutional norms and expectations align with the rules and values of dominant classes, students with higher levels of capital can better navigate the "hidden curricula" of these norms. Conversely, students from marginalized populations, who often have lower access to forms of capital, may face challenges accessing academic, social, and extracurricular opportunities and may receive fewer supports from their academic or governmental institutions (Adelman, 1993; Dennis et al., 2005; Estrada & Wang, 2017; Ishitani, 2006; Orbe, 2004; Stephens et al., 2012; Umansky, 2016). Limitations in access to capital, whether it be human, social, cultural, or financial, often results in lower outcomes for these students, including, but not limited to, lower grades (D'Amico & Dika, 2013; Michelmore & Dynarski, 2017), higher dropout rates (Ishitani, 2003, 2006, 2016; Martinez et al., 2009), and lower academic growth trajectories (D'Agostino & Rodgers, 2017; Kieffer, 2008).

Research over the past several decades has been devoted to understanding gaps in students' capital and ways disparities can be addressed. In some cases, studies document inequity in access to capital and how these may exacerbate and contribute to gaps in student outcomes.

Other research examines how particular programs, interventions, or policies may ameliorate gaps by providing greater access to wraparound services, mentoring supports, or resources and opportunities for these students (Carruthers & Fox, 2016; Schwartz et al., 2017; Shin, 2018; Vaughan et al., 2014). As the literature base grows, researchers and policymakers continue to make strides towards the goal of equity and inclusion of students from marginalized populations for whom inequities in capital persist due to structural inequities and barriers.

This three-study dissertation contributes to this growing body of literature by examining two large populations of historically marginalized populations, namely, English Learner (EL) students and first-generation college students, and their access to key forms of capital that affects their educational outcomes. The first study analyzes how ELs access human capital, operationalized as teacher characteristics and teacher effectiveness, and how this relates to their hazard of reclassification. As reclassification is a crucial outcome for ELs, this study aims to understand the relationship between characteristics of ELs' mainstream classroom teachers and ELs' rate of reclassification, as well as determine the measures of teacher effectiveness that may help identify effective teachers with respect to ELs' rate of reclassification. (Callahan, 2005; Callahan et al., 2009; Callahan & Shifrer, 2016; Johnson, 2019; Pope, 2016). Using discrete-time survival analysis methods, this study estimates the relationship between characteristics of ELs' mainstream classroom teachers and ELs' hazard of reclassification for students in grades 3-8 using longitudinal data from Tennessee. The study observes significant, positive effects on reclassification for ELs assigned to teachers of color. Moreover, measures of teacher effectiveness consistently predict EL reclassification. Sensitivity and robustness checks provide further evidence of these relationships.

Studies two and three turn attention to first-generation students, who are less likely to have access to sufficient social, cultural, and informational capital from parents to support their transition to college (Adelman, 1993; Atherton, 2014; Bui, 2002; Choy, 2002; Dennis et al., 2005; Engle, 2007; Inman & Mayes, 1999; Ishitani, 2006; Orbe, 2004; Stephens et al., 2012; Terenzini et al., 1996; Wildhagen, 2015). In contrast, degree-holding parents possess greater cultural and social capital around college-going and have more financial capital to support their children's pre-college development and college transition.

The second study takes a comprehensive look at the recent landscape of the first-generation college students enrolled in public institutions of higher education in Tennessee. Numerous scholars have examined the relationship between first-generation students access to cultural and social capital and their educational outcomes (Cragg, 2009; D'Allegro & Kerns, 2010; Fike & Fike, 2008; Ishitani, 2006, 2016; Nunez & Cuccaro-Alamin, 1998; Redford et al., 2017; Toutkoushian et al., 2019; Warburton et al., 2001). Yet, there remains a need to record differences in students' access to different levels of parental capital as it relates to granular outcomes of credit attainment. To this end, the second study uses institution fixed effects and a rich set of controls to document differences in first-generation and non-first-generation students' first-term credit and GPA outcomes. Subgroup analyses estimate differences in first-generation students based on level of parental education as well as differences between students for whom only their mother or only their father hold a college degree. Results substantiate prior findings, namely, that the "amount" of parental capital around college-going that students have access to matters for students' educational attainment.

The third chapter examines first-generation students' exposure to a statewide free-college scholarship and their first-term college outcomes. While the primary goal of the Tennessee

Promise is to guarantee eligible students the ability to attend a state public two-year institution tuition-free, the program arguably contributes much more to students, regardless of their ultimate participation in the program. The program recruits widely across the state, offers students one-on-one mentorship, provides a variety of informational supports, encourages FAFSA filing, and created a cultural shift around college going. In this way, I argue that the Tennessee Promise improves students’ access to human, cultural, financial, and social capital, which are critical determinants of students’ college access and choice (Perna, 2006, 2015). As first-generation students have a demonstrated need for financial and informational supports, they may benefit greatly from engagement with the Tennessee Promise. Using an interrupted time series approach, this study examines the extent to which first-generation students’ first-term postsecondary outcomes may have differed following the initiation of the Tennessee Promise. Estimates suggest the initiation of the Tennessee Promise is associated with an increase in first-generation students’ first-term credits attempted and credits earned, and an overall decrease in their first-term GPA. These changes appear somewhat greater for first-generation students compared to their non-first-generation peers and are concentrated in community colleges.

Chapters 2-4 below each contain a stand-alone study. Tables, figures, appendices, and references for each study are enclosed at the end of each chapter. Chapter 5 contains a concluding chapter summarizing findings and describing areas of future work.

References

Adelman, C. (1993). Insult, But No Injury: You Are Now a First-Generation College Student. *Educational Record; Washington*, *74*(1), 53.

Anyon, J. (1980). Social Class and the Hidden Curriculum of Work. *The Journal of Education*, *162*(1), 67–92.

Atherton, M. C. (2014). Academic Preparedness of First-Generation College Students: Different Perspectives. *Journal of College Student Development; Baltimore*, *55*(8), 824–829.

Barry, L. M., Hudley, C., Kelly, M., & Cho, S.-J. (2009). Differences in self-reported disclosure of college experiences by first-generation college student status. *Adolescence*, *44*(173), 55.

Berger, J. (2000). Optimizing capital, social reproduction, and undergraduate persistence. In J. M. Braxton (Ed.), *Reworking the student departure puzzle* (pp. 195–224). Vanderbilt University Press.

Bui, K. V. T. (2002). First-generation college students at a four-year university: Background characteristics, reasons for pursuing higher education, and first-year experiences. *College Student Journal*, *36*(1), 3–11.

Carruthers, C. K., & Fox, W. F. (2016). Aid for all: College coaching, financial aid, and post-secondary persistence in Tennessee. *Economics of Education Review*, *51*, 97–112. https://doi.org/10.1016/j.econedurev.2015.06.001

Carter, P. (2003). “Black” Cultural Capital, Status Positioning, and Schooling Conflicts for Low-income African American Youth. *Social Problems*, *50*, 136–155.

Choy, S. (2002). *Students Whose Parents Did Not Go to College: Postsecondary Access, Persistence, and Attainment: (492182006-021)* [Data set]. American Psychological Association. https://doi.org/10.1037/e492182006-021

Coleman, J. S. (1988). Social Capital in the Creation of Human Capital. In A. R. Sadovnik (Ed.), *Sociology of Education: A Critical Reader* (2nd ed., pp. 97–113). Routledge.

Collier, P. J., & Morgan, D. L. (2007). “Is that paper really due today?”: Differences in first-generation and traditional college students’ understandings of faculty expectations. *Higher Education*, *55*(4), 425–446. https://doi.org/10.1007/s10734-007-9065-5

Cragg, K. M. (2009). Influencing the Probability for Graduation at Four-Year Institutions: A Multi-Model Analysis. *Research in Higher Education*, *50*(4), 394–413. https://doi.org/10.1007/s11162-009-9122-2

D’Agostino, J. V., & Rodgers, E. (2017). Literacy achievement trends at entry to first grade. *Educational Researcher*, *46*(2), 78–89.

D’Allegro, M. L., & Kerns, S. (2010). Is There Such a Thing as Too Much of a Good Thing When it Comes to Education? Reexamining First Generation Student Success. *Journal of College Student Retention: Research, Theory & Practice*, *12*(3), 293–317. https://doi.org/10.2190/CS.12.3.c

D’Amico, M. M., & Dika, S. L. (2013). Using Data Known at the Time of Admission to Predict First-Generation College Student Success. *Journal of College Student Retention: Research, Theory & Practice*, *15*(2), 173–192. https://doi.org/10.2190/CS.15.2.c

Dennis, J. M., Phinney, J. S., & Chuateco, L. I. (2005). The Role of Motivation, Parental Support, and Peer Support in the Academic Success of Ethnic Minority First-Generation

College Students. *Journal of College Student Development*, *46*(3), 223–236. https://doi.org/10.1353/csd.2005.0023

Engle, J. (2007). Postsecondary access and success for first-generation college students. *American Academic*, *3*(1), 25–48.

Estrada, P., & Wang, H. (2017). Making English Learner Reclassification to Fluent English Proficient Attainable or Elusive: When Meeting Criteria Is and Is Not Enough. *American Educational Research Journal*, 000283121773354. https://doi.org/10.3102/0002831217733543

Fike, D. S., & Fike, R. (2008). Predictors of First-Year Student Retention in the Community College. *Community College Review*, *36*(2), 68–88. https://doi.org/10.1177/0091552108320222

Golann, J. W. (2015). The Paradox of Success at a No-Excuses School. *Sociology of Education*, *88*(2), 103–119. https://doi.org/10.1177/0038040714567866

Inman, W. E., & Mayes, L. (1999). The importance of being first: Unique characteristics of first generation community college students. *Community College Review; Raleigh*, *26*(4), 3.

Ishitani, T. (2003). A longitudinal approach to assessing attrition behavior among first-generation students: Time-varying effects of pre-college characteristics. *Research in Higher Education*, *44*(4), 433–449.

Ishitani, T. (2006). Studying Attrition and Degree Completion Behavior among First-Generation College Students in the United States. *The Journal of Higher Education*, *77*(5), 861–885. https://doi.org/10.1080/00221546.2006.11778947

Ishitani, T. (2016). First-Generation Students Persistence at Four-Year Institutions. *College and University, 91*(3), 22–33.

Jæger, M. M., & Karlson, K. (2018). Cultural capital and educational inequality: A counterfactual analysis. *Sociological Science*, *5*, 775–795. https://doi.org/10.15195/V5.A33

Johnson, I. (2008). Enrollment, Persistence and Graduation of In-State Students at a Public Research University: Does High School Matter? *Research in Higher Education*, *49*(8), 776–793. https://doi.org/10.1007/s11162-008-9105-8

Kieffer, M. J. (2008). Catching up or falling behind? Initial English proficiency, concentrated poverty, and the reading growth of language minority learners in the United States. *Journal of Educational Psychology*, *100*(4), 851–868. https://doi.org/10.1037/0022-0663.100.4.851

Lamont, M., & Lareau, A. (1988). Cultural capital: Allusions, gaps, and glissandos in recent theoretical developments. *Sociological Theory*, *6*(2), 153–168.

Martinez, J. A., Sher, K. J., Krull, J. L., & Wood, P. K. (2009). Blue-Collar Scholars?: Mediators and Moderators of University Attrition in First-Generation College Students. *Journal of College Student Development*, *50*(1), 87–103. https://doi.org/10.1353/csd.0.0053

Michelmore, K., & Dynarski, S. (2017). The Gap Within the Gap: Using Longitudinal Data to Understand Income Differences in Educational Outcomes. *AERA Open*, *3*(1), 2332858417692958.

Nunez, A.-M., & Cuccaro-Alamin, S. (1998). First-Generation Students: Undergraduates Whose Parents Never Enrolled in Postsecondary Education. *National Center for Education Statistics*, 100.

Orbe, M. P. (2004). Negotiating multiple identities within multiple frames: An analysis of first-generation college students. *Communication Education*, *53*(2), 131–149. https://doi.org/10.1080/03634520410001682401

Palmer, R., & Gasman, M. (2008). "It Takes a Village to Raise a Child": The Role of Social Capital in Promoting Academic Success for African American Men at a Black College. *Journal of College Student Development*, *49*(1), 52–70. https://doi.org/10.1353/csd.2008.0002

Pascarella, E. T., Pierson, C. T., Wolniak, G. C., & Terenzini, P. T. (2004). First-Generation College Students: Additional Evidence on College Experiences and Outcomes. *The Journal of Higher Education*, *75*(3), 249–284. JSTOR.

Perna, L. W. (2006). Studying College Access and Choice: A Proposed Conceptual Model. In J. C. Smart (Ed.), *Higher Education: Handbook of Theory and Research* (Vol. 21, pp. 99–157). Springer. https://doi.org/10.1007/1-4020-4512-3_3

Perna, L. W. (2015). Improving College Access and Completion for Low-Income and First-Generation Students: The Role of College Access and Success Programs. *University of Pennsylvania Scholarly Commons*, 14.

Redford, J., Hoyer, K. M., & Ralph, J. (2017). First-Generation and Continuing-Generation College Students: A Comparison of High School and Postsecondary Experiences. *National Center for Education Statistics*, 1–27.

Schwartz, S. E. O., Kanchewa, S. S., Rhodes, J. E., Gowdy, G., Stark, A. M., Horn, J. P., Parnes, M., & Spencer, R. (2017). "I'm Having a Little Struggle With This, Can You Help Me Out?": Examining Impacts and Processes of a Social Capital Intervention for First-

Generation College Students. *American Journal of Community Psychology*, n/a-n/a. https://doi.org/10.1002/ajcp.12206

Shin, N. (2018). The Effects of the Initial English Language Learner Classification on Students' Later Academic Outcomes. *Educational Evaluation and Policy Analysis*, *40*(2), 175–195. https://doi.org/10.3102/0162373717737378

Stephens, N. M., Fryberg, S. A., Markus, H. R., Johnson, C. S., & Covarrubias, R. (2012). Unseen disadvantage: How American universities' focus on independence undermines the academic performance of first-generation college students. *Journal of Personality and Social Psychology: Interpersonal Relations and Group Processes*, *102*(6), 1178–1197. http://dx.doi.org/10.1037/a0027143

Terenzini, P. T., Springer, L., Yaeger, P. M., Pascarella, E. T., & Nora, A. (1996). First-generation college students: Characteristics, experiences, and cognitive development. *Research in Higher Education*, *37*(1), 1–22.

Tobolowsky, B. F., Cox, B. E., & Chunoo, V. S. (2017). Bridging the Cultural Gap: Relationships Between Programmatic Offerings and First-Generation Student Benchmarks. *Journal of College Student Retention: Research, Theory & Practice*, *0*(0), 1–25. https://doi.org/10.1177/1521025117742377

Toutkoushian, R. K., May-Trifiletti, J. A., & Clayton, A. B. (2019). From "First in Family" to "First to Finish": Does College Graduation Vary by How First-Generation College Status Is Defined? *Educational Policy*, 089590481882375. https://doi.org/10.1177/0895904818823753

Umansky, I. M. (2016). Leveled and Exclusionary Tracking: English Learners’ Access to Academic Content in Middle School. *American Educational Research Journal*, *53*(6), 1792–1833. https://doi.org/10.3102/0002831216675404

Vaughan, A., Parra, J., & Lalonde, T. (2014). First-Generation College Student Achievement and the First-Year Seminar: A Quasi-Experimental Design. *Journal of The First-Year Experience & Students in Transition*, *26*(2), 51–67.

Warburton, E. C., Bugarin, R., & Nuñez, A.-M. (2001). *Bridging the Gap: Academic Preparation and Postsecondary Success of First-Generation Students* (NCES 2001-153; Postsecondary Education Descriptive Analysis Reports, p. 83). U.S. Department of Education Office of Educational Research and Improvement.

Wildhagen, T. (2015). “Not Your Typical Student”: The Social Construction of the “First-Generation” College Student. *Qualitative Sociology*, *38*(3), 285–303. https://doi.org/10.1007/s11133-015-9308-1

Willis, P. (1981). *Learning to Labor: How Working-Class Kids Get Working Class Jobs* (Morningside edition). Columbia University Press.

Chapter 2

Learning Language in the Mainstream: Unpacking the Relationship Between Classroom Teacher Characteristics and Time to English Learner Reclassification

English Learners (ELs) are among the fastest growing student subgroups in the country—increasing in population by 1.2 million students, or 32 percent, between 2000 and 2017 and making up about 10 percent of all public school students nationwide (National Center for Education Statistics, 2020). ELs are students whose native language is non-English and who score below proficient on an English proficiency exam. ELs are retested annually and are reclassified as English proficient upon meeting state-determined criteria. For ELs, becoming English proficient is a crucial goal for academic progress; not only does proficiency in English help ELs access class content and college-track coursework (Callahan, 2005; Callahan et al., 2009; Callahan & Shifrer, 2016), but it has also been found to increase ELs' likelihood of on-time graduation and college attendance (Johnson, 2019) and is associated with higher ACT scores and GPAs for ELs (Carlson & Knowles, 2016; Pope, 2016).

Amongst the school resources that support ELs' development of English language proficiency, the mostly commonly recognized are ESL programs and ESL teachers (Bunch, 2013; Callahan & Shifrer, 2016; Garrett et al., 2019; Lucas et al., 2008; Umansky & Reardon, 2014). However, many ELs spend a large portion of their academic time with mainstream classroom teachers in core subjects. Greater percentages of mainstream teachers across the country also report having ELs in their classrooms. This shift is likely due to changes in immigration and migration patterns and a greater push towards integrated education for student subgroups (Hakuta & Pecheone, 2016; Quintero & Hansen, 2017; *Schools and Staffing Survey 2011-12*, 2012; Zehler et al., 2003). Therefore, in addition to receiving English language instruction from ESL programs, ELs may also receive instruction in the English language from their mainstream teachers. Though we know much about the characteristics of ELs themselves that relate to their rates of reclassification (Garrett et al., 2019; Mavrogordato & White, 2017; Motamedi et al., 2016; Slama, 2012; Thompson, 2017), we know very little about the mainstream classroom teachers ELs experience as they progress through school and the role these teachers may play in developing ELs' English language proficiency.

Mainstream teachers' experiences and skills matter for EL achievement. Recent work on the role of ELs' mainstream classroom teachers documents the relationship between characteristics of ELs' mainstream classroom teachers and EL's achievement on standardized tests in reading and math, finding that ELs have higher test scores when assigned to teachers with skills and experiences aligning with the unique learning needs of ELs (e.g. proficiency in ELs' native language) (Masters et al., 2016; Loeb et al., 2014). This work also finds that some teachers are more effective in improving ELs' test scores relative to those of non-ELs (Masters et al., 2016; Loeb et al., 2014). However, other studies have also documented that mainstream teachers may be less qualified and less prepared to teach ELs, lacking appropriate certifications and training (Esch et al., 2005; Gándara et al., 2003; Harper et al., 2008; Lucas, 2011; Lucas & Grinberg, 2008; Lucas & Villegas, 2010; Ruiz Soto et al., 2015; Rumberger, 2003). Researchers and practitioners alike are calling for improvements in classroom teacher preparation to create a workforce that is better equipped to teach EL students in their classes (de Jong et al., 2013, 2013; Karabenick & Noda, 2004; Loeb et al., 2014; López et al., 2013; Lucas et al., 2008; Lucas & Grinberg, 2008; Lucas & Villegas, 2010).

Given the growing population of EL students and the important role that mainstream classroom teachers play in students' development, it is important to understand the relationship between characteristics of ELs' mainstream classroom teachers and ELs' rate of reclassification, as well as which measures of teacher effectiveness may help in identifying highly effective teachers with respect to ELs' rate of reclassification. While math teachers characteristics have been found to be positively relate to ELs' math scores (Masters et al., 2016), reading teacher characteristics likely matter more with respect to ELs' language acquisition as reading teachers explicitly teach language skills such as grammar, comprehension, vocabulary, and fluency. As such, this study focuses on ELs' mainstream reading teachers. This study asks the following research questions:

1. What characteristics of mainstream reading teachers relate to ELs' rate of reclassification?
2. How do measures of teacher effectiveness for mainstream reading teachers relate to variation in ELs' rate of reclassification?

Drawing from a unique longitudinal administrative dataset from Tennessee containing information on EL students, their mainstream classroom teachers, and peers, as well as various measures of teacher effectiveness obtained through the state's teacher evaluation system, this study estimates the relationship between characteristics of ELs' mainstream classroom teachers and ELs' hazard of reclassification for students in grades 3-8, employing discrete-time survival analysis methods. The study observes significant, positive effects on reclassification for ELs assigned to teachers of color. However, these findings are not observed across all models. Instead, this study finds that measures of teacher effectiveness consistently predict EL reclassification. Sensitivity and robustness checks provide further evidence of these relationships, though findings from these checks suggest estimates should be interpreted with caution.

Unlike prior work on EL reclassification, which uses data from large, urban areas with substantial numbers of EL students (e.g. California, Texas, New York), the present study uses data from Tennessee, where ELs' learning environment is more representative of that experienced by the average ELs in the country, (i.e. suburban and rural, with relatively lower concentrations of EL peers). This study contributes to the growing body of work on EL teachers and EL reclassification and is among the first to document the relationship between mainstream teachers and reclassification. Findings from this study also have important policy implications for the assignment of ELs to mainstream teachers and the identification of effective mainstream teachers for ELs.

Literature

Current literature examining teacher characteristics and student outcomes has identified a number of ways in which teachers impact their students' learning outcomes (Borman & Kimball, 2005; Boyd et al., 2009; Clotfelter et al., 2007; Darling-Hammond, 2000; Nye et al., 2004; Phillips, 2010; Rivkin et al., 2005; Rockoff, 2004; Stronge et al., 2011; Taylor et al., 2010). Studies have found teacher traits such as teachers' standards-based evaluation ratings (Borman & Kimball, 2005; Darling-Hammond, 2000; Gershenson, 2016; Rivkin et al., 2005; Rockoff, 2004; Taylor et al., 2010), pre-service preparation (Boyd et al., 2009; Rockoff et al., 2011), verbal skills (Ehrenberg & Brewer, 1995; Hanushek, 1992), years of experience (Clotfelter et al., 2010; Rockoff, 2004), degrees and coursework (Rockoff et al., 2011; Wayne & Youngs, 2003), and licensure (Clotfelter et al., 2010) to be positively associated with math and reading test scores and student attendance.

It is natural, then, to expect that mainstream teachers influence ELs' language development. A small, but growing body of literature finds that teacher characteristics matter for EL outcomes. In a year-long study of ELs enrolled in a bilingual kindergarten program in three states, teacher effectiveness, measured through teacher observations, was found to be positively associated with measures of student engagement. Teachers' oral language proficiency in both Spanish and English predicted measures of student performance, though the observation measure was less related (Cirino et al., 2007).

While the previous study examined the unique context of ELs in a bilingual classroom, two studies have examined the characteristics of mainstream teachers on ELs' test score outcomes. Loeb et al. (2014) examine ELs' access to effective teachers by calculating teacher value-added scores for teachers' EL and non-EL students using standardized test scores in reading and math. They find that teachers who are effective with ELs are also effective with non-ELs, and vice versa. Moreover, the authors find that teachers fluent in EL students' home language or those with a bilingual teaching certification are actually more effective with their EL than with their non-EL students.

A follow-up study by Master et al. (2016) builds on the prior work of Loeb et al. (2014) by first examining the relationship between traditional characteristics of effective teachers and EL and non-EL students' math achievement, and second, examining whether teachers with different training or experience with ELs are differentially effective with their ELs relative to their non-ELs.[1] After controlling for student and classroom characteristics, the study finds few differences in teacher effects on ELs relative to non-ELs when looking at teachers' own standardized test scores and years of experience. But, novice teachers with prior experience

[1] Only math outcomes were examined in this study due to limitations in the available English Language Arts (ELA) test data.

teaching ELs were found to be more effective in improving their ELs' math test scores relative to those of their non-EL students. In addition, teachers who reported receiving nine or more hours of in-service professional development on EL instructional strategies in the beginning of their first year of teaching had greater differential efficacy with ELs in that year, compared to teachers who did not receive such training.

Findings from these studies underscore that mainstream teacher experiences and skills impact the educational experiences and outcomes of their EL students. These papers also make an important policy recommendation for ELs to be assigned to mainstream classroom teachers who are more effective. As Loeb et. al. (2014) note, "finding a better teacher for ELs is at least as much if not more a question of finding an effective teacher, as it is a question of finding a teacher who specializes in ELs" (p. 469).

Nevertheless, as emphasized by many scholars, mainstream teachers may be unprepared to appropriately meet the learning needs of linguistically diverse students (Harper et al., 2008; Lucas & Grinberg, 2008; Lucas & Villegas, 2010). For example, two recent reports studying ELs in California, the state with the largest EL population in the country (Ruiz Soto et al., 2015), found that ELs are more likely to be taught by teachers who lack the appropriate training or credentials to support their unique learning needs (Bunch, 2013; Esch et al., 2005; Gándara et al., 2003; Rumberger, 2003). These reports found that, as of 2005, 25-50 percent of the teachers of EL students were not fully certified to teach them. California now requires that all mainstream classroom teachers hold a certification to provide instruction for these learners and all candidates enrolling in California teacher preparation programs automatically earn the certification (Commission on Teacher Credentialing, 2018, 2019; Office of English Language Acquisition Services, 2020). Despite this change, less experienced or less senior teachers are still more likely to be placed into teaching EL content courses, as more senior teachers choose not to teach these courses or may not hold the EL certification that California law now requires of all teachers (Dabach, 2015). In recent years, researchers and practitioners alike are calling for improvements in classroom teacher preparation to create a workforce that is better equipped to teach EL students in their classes (de Jong et al., 2013, 2013; Karabenick & Noda, 2004; Loeb et al., 2014; López et al., 2013; Lucas et al., 2008; Lucas & Grinberg, 2008; Lucas & Villegas, 2010).

Context

The below description of EL policy in Tennessee provides context for how the state processed ELs in the time the study takes place, from the 2005/06 through the 2014/15 school years. Tennessee's EL population is rapidly growing. As seen in Figure 1-1, between 2006 and 2015, the state's EL population more than doubled, from 14,293 to 37,322. Per federal policy, Tennessee districts are required to administer a home language survey to all students who enroll in a Tennessee public school (Every Student Succeeds Act, 2015; U.S. Department of Education, 2016). The survey asks parents/guardians to identify the first language the child learned to speak, the language the child speaks most often outside of school, and the language most people speak inside the child's home. If the response to the survey is "English" to all survey questions, the child is not required to be screened for English proficiency. If at least one response is a language other than English, the English proficiency of the child was assessed using the Tennessee

English Language Placement Assessment (TELPA).[2] Students scoring a 1 or 2 (out of 3) on the TELPA receive ESL services. Students scoring a 3 on the TELPA do not qualify for services.[3]

Upon receiving EL status, students receive a variety of language-development services and supports from the school to help develop English language proficiency. Commonly, students are placed in ESL programs in their schools. ESL programs vary across schools in terms of the way English language instruction and academic content is delivered. These classes are generally taught by a certified ESL teacher with specialized training to work with EL students. Districts in Tennessee can select from one of six types of ESL program delivery models, including:

- Sheltered English instruction,
- Structured English immersion,
- Specially designed academic instruction in English,
- Content-based English instruction,
- ESL Pull-out instruction, or,
- ESL Push-in or inclusion

To help ELs access the academic content, teachers may provide ELs with modified tests, instruction, or assignments, additional scaffolding during lessons, various accommodations, or interventions (e.g. Response to Intervention (RTI) programs).

During February or March of the 2006/07 through the 2013/14 school years, ELs' language proficiency was tested annually using the English Language Development Assessment (ELDA). Reclassification decisions were made at the end of the spring term using students' scores on the ELDA. ELs with a composite score of 5 were automatically reclassified as English language proficient, while students scoring a 4 may be reclassified as English language

[2] In the 2014/15 school year, Tennessee switched from using the TELPA to identify ELs to using assessments provided by the WIDA Consortium. The W-APT is now used to identify kindergarten students who are ELs and the WIDA Screener is used to identify newly enrolling students in grades 1-12.
[3] Parents who wish to waive services for their child may opt to do so, but these students are still tested annually to track their language development.

proficient. If an EL with a composite score of 4 was not reclassified, their name was to be reported to the state, along with the reason the student was not reclassified. (*Overview of Title III English as a Second Language: Service Requirements for Non-English Background Students*, 2013).[4] Upon reclassification, ELs stop receiving specialized language services from an ESL teacher and ceased taking the ELDA exam in spring.

Empirical Strategy

This study uses discrete-time survival analysis techniques to estimate the relationship between characteristics of ELs' mainstream classroom teachers and ELs' hazard of reclassification at a given time for students in grades 3-8 using longitudinal data from Tennessee (Singer & Willett, 2003). Building on traditional regression analyses, discrete-time survival analyses allow models to predict not only the likelihood of reclassification as is estimated in traditional logistic models, but also *when* students are most likely to be reclassified (Box-Steffensmeier et al., 2003; Mavrogordato & White, 2017). The analysis relies on calculating the hazard function, which estimates the instantaneous probability that a student will be reclassified in a given school year, conditional on the fact that the student was not reclassified in prior years. In this way, the hazard function captures how an EL's likelihood of reclassification changes over time for students who have not yet been reclassified.

Data

This study relies on nine years of Tennessee administrative data, collected by the Tennessee Department of Education (TDOE), and maintained by the Tennessee Education

[4] Beginning in the 2014/15 school year, Tennessee adopted the WIDA standards for EL education (Tennessee Department of Education, 2016). The state changed to using the WIDA language screeners (W-APT and WIDA Screener) and assessment of language proficiency (WIDA ACCESS 2.0) starting in 2015/16 (Tennessee Department of Education, 2018).

Research Alliance (TERA), a research practice partnership between the TDOE and Vanderbilt University's Peabody College of Education. The database contains student- and teacher-level information from the 2005/06 to the 2014/15 school years in Tennessee[5], including student and teacher demographic characteristics, student's EL status within each year, measures of teacher effectiveness collected from the state's teacher evaluation system, student-teacher linkage files, and information on teacher positions with a school. The data also contains records of students' standardized achievement test scores for reading and math on the Tennessee Comprehensive Assessment Program (TCAP), the state's end of year standardized assessment for grades 3-8.

Measures

Dependent Variable

The outcome of interest is ELs' likelihood of reclassification. This outcome is denoted as a conditional failure, or hazard rate, which is a latent variable measuring students' risk process for reclassification. The hazard rate is the rate at which an EL student is reclassified by time *t* (measured in school years), given that the student has not yet been reclassified by time *t*. In other words, the hazard rate is the instantaneous rate of reclassification at time *t*, ignoring the accumulation of the hazard of reclassification up to time *t*. The data used to calculate the hazard rate is a binary variable equal to 0 when a student is classified as an EL and equal to 1 in the year in which he or she is reclassified as a non-EL. This binary variable was derived based on each student's EL classification in the following school year. For instance, if in the data, a student's EL status was "EL" from 2006/07 – 2009/10 school years and then "non-EL" in the 2010/11 school year, the student was said to be reclassified during 2009/10 (though the reclassification decision would have been made in the spring at the end of the academic year). Since data on EL

[5] In this study, the lagging year is used to refer to a school year. Thus, "2015" represents the 2014/15 school year.

students' English proficiency levels are updated annually in spring, the measure of time is discrete, measured in academic school years (fall through spring). In order to account for students who are retained in a grade level, time is measured as the number of years a student is observed starting in third grade onward, and an indicator is included in analytic models for whether a student was retained in the prior year.

Independent Variables

The two types of independent variables examined in this study are measures of teacher characteristics and measures of teacher effectiveness. These measures have been identified as teacher factors associated with outcomes important to ELs, such as English literacy or standardized test achievement (Borman & Kimball, 2005; Boyd et al., 2009; Clotfelter et al., 2007; Darling-Hammond, 2000; Ehrenberg & Brewer, 1995; Gershenson, 2016; Hanushek, 1992; Nye et al., 2004; Phillips, 2010; Rivkin et al., 2005; Rockoff, 2004; Stronge et al., 2011; Taylor et al., 2010; Wayne & Youngs, 2003).

Teacher Characteristics. Measures of teacher characteristics include variables for teacher race/ethnicity, education, and years of experience. Since most EL teachers in Tennessee are White, teacher race/ethnicity is measured as a binary indicator equal to one when a teacher is a teacher of color. Teacher education is measured as a binary indicator equaling one for teachers who held a master's degree or higher, and zero if a teacher's highest degree was a bachelor's or less. Teachers' years of experience is measured as a continuous variable transformed by dividing years of experience by 10, resulting in a variable ranging from 0 to 4.9, increasing in units of 0.1 (where 0.1 is equal to one year). This transformation was made for ease of interpretability, as the coefficient is quite small when years of experience is measured in units of one year.

Teacher Effectiveness. Five measures of teacher effectiveness are used, each derived from teacher value-added models (VAMs) and observation scores. In 2011, Tennessee adopted the Tennessee Educator Acceleration Model (TEAM), a teacher evaluation and observation system collecting data on teacher value-added scores and observations. TEAM data are available from the 2011/12 through 2014/15 school years.

Though value-added models are widely used in the research and policy arenas, numerous scholars have highlighted issues with VAMs, such as measurement error, non-random assignment of students and teachers, and instability in the measures over time, among others (Ballou & Springer, 2015; Goldhaber & Hansen, 2013; Guarino et al., 2015; Darling-Hammond et al., 2011). Another oft-mentioned limitation of value-added is the fact that they only measure students' test-score growth, and may not measure other important behaviors and skills of teachers that may not be picked up in test scores, such as creating classroom culture or incorporating meaningful content into the classroom (Cohen & Goldhaber, 2016).

Measures such as classroom observation scores may capture additional information about teacher effectiveness not included in value-added scores (Steinberg & Garrett, 2016) and may have high face validity. However, observation scores come with their own set of challenges. Scores may be affected by evaluator bias or variation in rater scores due to the cognitive demands of conducting classroom observations (Cohen & Goldhaber, 2016). Scores may also be affected by the nonrandom sorting of students to teachers (Steinberg & Garrett, 2016), and are only loosely correlate over time (Garrett & Steinberg, 2015). Furthermore, observation instruments often do not lead to a distribution of ratings, and historically, most teachers are rated effective or highly effective (Cohen & Goldhaber, 2016). Given the tradeoffs between value-added and observations scores, this analysis examines the relationship between students' hazard of reclassification and both types of measures. The analysis also considers composite measures, which incorporate multiple measures of teacher effectiveness.

Value-Added Scores. Teacher value-added scores (TVAAS) are calculated for tested-subject teachers using their students' value-added scores on the Tennessee Comprehensive Assessment Program (TCAP) end of year exam. The state converts each TVAAS score into a TVAAS index by dividing the value-added (TVAAS) score by the standard error. Thus, two teachers with the same TVAAS score may have different TVAAS indices if the standard errors differ. Standard errors are estimated with more precision when a teacher teaches more students (Hunter, 2018).

The state also creates three-year composite value-added indices (TVAAS), which are created by taking the average of teachers' year-grade-subject indexes within the past three years, weighting each index by the number of students contributing to the estimate.[6] As the three-year composite measure contains cumulative information on teachers overall measure of effectiveness, it is this three-year composite TVAAS index that is used in the analysis. The value-added composite score is measured both as a continuous measure as well as a categorical measure of value-added effectiveness level, also created by the state. TVAAS levels 1-5 correspond to 3-year composite index scores of $(-\infty, -2)$, $[-2, -1)$, $[-1, 1)$, $[1, 2)$, and $[2, \infty)$, respectively. Using teachers' prior year value-added (TVAAS) levels, teachers in levels 1-2 are defined as "Less Effective", teachers in level 3 as "Average Effectiveness", and teachers in levels 4-5 as "Highly Effective" for the purposes of this analysis (Hunter, 2018).

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[6] Documentation from the Tennessee Department of Education states that three-year evaluation composite scores include data within the past three years of subjects and grade levels taught "when available" (Tennessee Department of Education, 2013). This indicates that the three-year evaluation composite score for teachers who have fewer than three years of data for a given subject will only contain one or two years of TVAAS data.

Observation Scores. In addition to calculating teacher value-added scores, Tennessee also collects data on teacher observations. Observation scores are available for most teachers. The majority (over 85 percent) of districts in Tennessee conduct annual observations of their teachers using the state's TEAM observation rubric, which is similar in nature to the TAP rubric designed by the National Institute for Excellence in Teaching (Hunter, 2018). On the TEAM rubric, teachers are observed on four domains of, namely, instruction, environment, planning, and professional, within which are multiple indicators. Teachers are observed multiple times a year by certified observers and receive a score of 1 through 5 on each of the 19 TEAM rubric indicators across the four domains. Teachers' indicator scores are then averaged together within an academic year to assign each teacher an overall average observation score. As the mean of teacher's score across all indicators within a given school year, the average observation score is continuous.

To ease the interpretation of this variable, indicators for whether a teachers' average score fell into the top-most, middle two, or bottom quartiles of teacher scores within a given year are created for the purposes of this analysis. In addition, teachers in some districts are observed using alternate observation systems, though these systems are similar to TEAM and teachers in districts using alternate systems still receive an overall average observation score. To account for any variation in scores across observation systems, a binary indicator for whether the teacher was observed on the TEAM or an alternate rubric is included in analyses using observation scores. The low correlation of 0.26 between the observation score and the value-added composite score shown in Table 1-1 suggests these two measures are picking up differing behaviors of teachers.

Overall Level of Effectiveness. Using the teacher value-added and observations scores, teachers in Tennessee receive an overall level of effectiveness (LOE) score created by the state.

This score is a composite measure of teacher effectiveness constructed using both the value-added (TVAAS) and observations scores mentioned above, as well as teachers' achievement scores within individual subjects taught and student surveys (Hunter, 2018).[7] These components are combined to create a continuous level of effectiveness score that is then transformed into a discrete five-category scale. The composite LOE measure places teachers into one of five categories of effectiveness ranging from a score of (1) for significantly below expectations to (5) significantly above expectations. Similar to the transformation of the TVAAS score into TVAAS levels, teachers' LOE scores are categorized where teachers with scores of 1-2 are defined as "Less Effective", level 3 as "Average Effectiveness", and levels 4-5 as "Highly Effective". While TVAAS scores are only available for tested-area teachers, overall LOE scores are available for most teachers, since almost all teachers receive a formal teacher observation.

A caveat about how the LOE scores are constructed is important to note. As shown in Table 1-1, the correlations between the LOE score and the value-added and observation scores are 0.65 and 0.53, respectively, in the sample, and 0.64 and 0.51 in the full population. Given that the LOE score is comprised of both the value-added and observation score, a moderate positive correlation between these values makes sense. The higher correlation between the LOE and composite value-added score can be explained by the fact that, starting 2011/12, teachers receiving a TVAAS level score of level 3 or higher could replace the achievement component of their LOE score with their value-added score. Additionally, starting in 2013, teachers receiving a TVAAS level score of 4 or higher could override their LOE score with their value-added level score. As such, for some higher performing teachers, their LOE and TVAAS level scores are

[7] There is some variation in how the overall level of effectiveness is calculated for tested and non-tested subject area teachers.

identical. Binary indicator variables are included in analyses using LOE scores for whether a teacher made use of either of these rules.

In total, five measures of teacher effectiveness are used: (1) a continuous measure of teachers' three-year composite value-added score (TVAAS), (2) teachers' level of effectiveness based on their three-year composite value-added score (TVAAS Level), (3) a continuous measure of teachers' average observation score, (4) teachers' observation quartiles, and (5) a categorical measure of teachers' overall level of effectiveness (LOE) score. Each measure is lagged using a teachers' score in the prior year.

Control Variables

Control variables include student characteristics that may be associated with students' likelihood of reclassification as observed in prior literature (Mavrogordato & White, 2017; Motamedi et al., 2016; Slama, 2012; Thompson, 2017). Student-level characteristics include race/ethnicity, sex, special education (SPED) status, immigrant status, and whether a student was retained in the prior year. Student race/ethnicity is a categorical variable for whether a student was White, Black, Latinx, or Asian/other race, where the reference category is Latinx. Sex, SPED, immigrant, and retention status are all binary indicators.

These student characteristics were also aggregated to the "classroom" level to account for peer characteristics and/or classroom environmental characteristics that may be associated with students' likelihood of reclassification. In the absence of true classroom-level identifiers, a "classroom" is defined as the group of students assigned to a teacher within a given school, year, and grade. A students' classroom peers are the characteristics of the other students in the "classroom", excluding the characteristics of the student himself. These variables may reflect the way teaching practices reflect the students assigned to them, the interactions students may have with peers, or other aspects of a students' learning environment that is related to reclassification. Classroom characteristics include the number of peers assigned to their reading teacher within a given school, grade, and year, as well as the percent of a student's peers who receive SPED services, and the percent who are ELs.

Samples

Since a primary goal of the study is to examine the relationship between measures of teacher effectiveness and EL students' time to reclassification, creating a sample that can speak to both teacher characteristics and measures of teacher effectiveness is critical to this analysis. However, teacher value-added measures are not available for teachers in grades K-2. As such, this analysis prioritizes the creation of a sample that includes teachers with value-added scores. Since value-added scores are only available for teachers in grades 3 and onward, one possibility would be to construct the analytic sample for all 3rd grade EL students who are able to be matched to teachers. However, this may introduce bias into the estimates since such a sample would likely include students who experienced schooling outside of the state prior to third grade and who entered the Tennessee school systems starting in grade 3. Thus, the sample may include students who experienced schooling in other states or countries, or students who may have experienced additional changes or challenges in their life, such as immigrating to the country as a refugee later in their childhoods. These experiences are likely to be related to their rate of language acquisition.

Instead, a sample is constructed of cohorts of EL students who began kindergarten in the state as ELs between 2005/06 through 2011/12, and who were still classified as ELs in third grade onward (2008/09 through 2014/15) and in years in which lagged measures of teacher effectiveness are available. By constructing cohorts of students who began school in Tennessee in kindergarten, some of the variation in the educational experiences of students prior to third grade is removed, and prior schooling is controlled for using students' third grade standardized test score in reading. In constructing the sample in this way, students who were reclassified before or by the end of third grade, or who left the sample before third grade, are also removed, representing approximately 35 percent of the 20,226 unique ELs who started kindergarten in Tennessee between 2005/06 through 2011/12.

Using information on students' annual EL status and grade level, students who started in the state of Tennessee as ELs in kindergarten and who were still consecutively enrolled as ELs in third grade onward were maintained in the sample. Cohort dummies are created indicating the year in which a student first enrolled in third grade. If students left the data following third grade and then reentered, the observations following the last consecutive year the student was observed were removed. Reclassification is defined as whether a student was reclassified during the following year. For students who were never reclassified between grades 3-8, the last year the student was consecutively observed in the data is identified. A binary variable was then created to equal one for the school year in which the student was reclassified in spring. A time variable was also created equaling the number of years following third grade after which the student was reclassified, or, if a student was never reclassified between grades 3-8, the last year the student is consecutively observed. Observations following the first year in which a student is reclassified are removed. This procedure results in a student-level person-period dataset used in the main analysis. To examine the life table displaying students' hazard of reclassification in each grade, the person-period dataset is modified such that last observation for a given student was retained.

To create the main analytic sample, a set of student-teacher linkage files are used to match EL students to their reading teachers. These student-teacher linkage files are available for all teachers who are evaluated by the state's teacher evaluation system. Use of the teacher evaluation system is mandatory for public school teachers in the state from grade 3 onwards. Since ELs may be assigned to multiple teachers for reading instruction (e.g. mainstream reading and ESL teachers), it was important to identify which ELs received language instruction from a mainstream reading teacher and which students received instruction from both a mainstream reading teacher and an ESL teacher. ELs who only received instruction from an ESL teacher in a given year were identified and omitted, representing 20 percent of matched student observations, since the focus of this analysis is on the relationship between mainstream reading teachers of ELs.

First, student-teacher linkage, teacher, and staff role files were merged together. Using claims data of student time and availability reported by teachers each year, student-teacher links for students' reading teachers were retained in the sample when a teacher claimed more than 0 percent of a student's time in reading and when a student was listed as being fully or partially available in a teacher's classroom in reading. Next, three groups of teacher-student linkages were identified: (1) students who have both ESL and mainstream teachers claiming their time in reading, (2) students who only have a mainstream teacher(s) claiming their time in reading, and (3) students who only have ESL teacher(s) claiming their time in reading. Students who only have ESL teacher(s) claiming their time in reading were removed since the goal of this analysis is to examine mainstream classroom teachers. For students who had multiple mainstream teachers claiming their time in reading within a given school year (e.g. if a student had one teacher for reading and another for writing), the teacher that claimed the largest percentage of their time was retained in the sample. For the handful of ties in the percent of students' time claimed, one teacher was randomly dropped. A flag variable was created identifying the students that had both a mainstream and an ESL teacher in the same school year, and the characteristics of their ESL teachers were removed from the analysis. Finally, the student-teacher linkage file, student demographic, classroom characteristics, teacher characteristic, and teacher effectiveness files were combined.

Since most teachers receive an observation and LOE score, while only tested-subject teachers receive a value-added score, two analytic samples were created. The first sample contains data on students assigned to teachers who have observation and LOE scores (LOE Sample) (N=10,189). The second sample contains data on students assigned to teachers who have TVAAS scores (N=7,497) (TVAAS Sample). Almost all teachers that had a TVAAS score had an observation score as well (N=6,731). In general, this analysis uses a sample following seven cohorts of students who were third graders in 2008/09 through 2014/15, following students from 2012/13 through 2014/15, depending on the cohort. A student's cohort is the year in which he or she started third grade for the first time. Since multiple panels of students are used, and one-year lagged data on teacher effectiveness is available starting in 2012/13 and is unavailable after 2015, there are different cohorts used in the analysis for each grade, as shown in Panel A of Table 1-2 for the TVAAS sample and Panel B for the LOE sample. For instance, in the analysis using value-added scores (Panel A), estimates for reclassification in grade 3 rely on students in cohorts who started third grade in the 2013, 2014, and 2015 school years, while estimates for reclassification in grade 8 rely on students in cohorts who started third grade in the 2009 and 2010 school years.

Column 1 of Table 1-3 shows summary statistics for students, teachers, and classrooms in the value-added score (TVAAS) sample, and column 2 shows statistics for the LOE sample. Characteristics are comparable across the two samples. Statistics are discussed for the LOE composite, as it is the larger sample. Almost 90 percent of students are observed between grades 3-5. Approximately 83 percent of EL are in cohorts starting third grade in 2010/11 through 2014/15. Since lagged teacher effectiveness measures are only available starting in 2012/13, fewer students in the sample are from cohort years 2009 and 2010. These students had to remain ELs until 2012/13 or remain in Tennessee public schools to be linked to a teacher with prior year measures of teacher effectiveness.

Over 90 percent of students in the sample are eligible for FRPL, 86 percent are Latinx, and 13 percent are immigrants who arrived prior to starting kindergarten. Teachers in the sample are mostly female and White, with only a quarter of teachers being teachers of color.[8] Most teachers have a master's degree or higher and are ELs' only formal reading teacher. While 64.37 percent of ELs' peers are students of color, there is an equal division between peers who are Black (31.13 percent) and Latinx (30.26 percent). ELs' mainstream teachers are likely to be effective (22.94 percent) or highly effective (66.43 percent) based on LOE scores and are similarly more likely to be effective or highly effective based on their value-added scores.

Characteristics of students in the sample were also compared to the population of ELs in the state who can be matched to teachers, as shown in Table 1-4. Characteristics of students in the sample and population were similar. Any differences in the characteristics of students in the sample and the population of ELs is largely by design. Students in the sample were more likely to be eligible for FRPL, less likely to be more immigrants, more likely to be Latinx, and slightly less likely to be retained. This is expected as the sample removes students who immigrate

[8] Appendix Table A1-1 shows the roles of teachers in the analytic samples according to data in the TERA staff files. In both the TVAAS and LOE samples, over 80 percent of teachers were grade 3-8 teachers. Other roles include teachers in grades K-2, general education "elementary" or "secondary" teachers. A small percentage of teachers are identified as other specialized teachers, which could be a function of teacher assignment in a particular school, teachers holding multiple positions in a school, or issues of administrative data.

following kindergarten. Since the sample removes students who only were assigned to an ESL teacher in a given school year, it is similarly expected that more students in the sample had both a mainstream and an ESL teacher. Given the larger percentage of students in the sample who are eligible for FRPL and Latinx, it is similarly expected that students' peers were also more likely to be eligible for FRPL and Latinx. The distribution of teacher effectiveness scores in the population and in the sample are relatively comparable.

Analysis

This study uses discrete-time survival analysis techniques to model the relationship between covariates and a given event, namely, students' hazard of reclassification, at a given point in time (Singer & Willett, 2003). Building on traditional regression analyses, discrete-time survival analyses allow models to predict not only the likelihood of reclassification as is estimated in traditional logistic models, but also *when* students are most likely to be reclassified (Box-Steffensmeier et al., 2003; Mavrogordato & White, 2017). Another advantage is that survival analyses use data from both students who experience and do not experience the event in the timespan examined, while traditional logistic models omit these observations. Finally, since risk is calculated for each distinct time period, survival analyses allow for students who have missing data in one time period to be included in years when data are complete.

Survival analyses rely on two distributional functions, the survivor function and the hazard function. The survivor function, *S(t)* function estimates the probability that a student will survive (or fail to be reclassified) longer than time *t.* In other words, the survivor function captures whether an EL will remain classified as an EL beyond a particular school year. The hazard function estimates the instantaneous probability that a student will be reclassified in a given school year, conditional on the fact that the student was not reclassified in prior years. The hazard function captures how an EL's likelihood of reclassification changes over time for students who have not yet been reclassified. The multivariate models explain how covariates are associated with a students' hazard rate (Mavrogordato & White, 2017; Singer & Willett, 2003; Thompson, 2017). This study specifies the hazard function as a discrete-time proportional hazard model where time is divided into discrete, equal increments, rather than continuous as, is the case in a Cox proportional hazard function. The measure of time is the number of school years since third grade, since reclassification decisions are made at the end of a given school year. The discrete-time hazard model makes use of the logit-link transformation, resulting in results predicting the logarithm of the odds of reclassification within each year following third grade.

The parametrization of time is a key aspect of discrete-time survival analyses, as ELs' risk of being reclassified is dependent on how long the student has been an EL. Baseline hazard specifications with different parametrizations of time were compared. Since models are not nested, the Bayesian information criterion (BIC) statistic was used to compare fit across models. Time was defined as being constant, linear, quadratic, cubic, quartic, or unrestricted. The model with the lowest BIC is preferred. Table 1-5 presents different hazard specifications and the resulting BIC statistics. Since the unrestricted specification has the lowest BIC of 8829.652, dummy variables representing the number of years since third grade (where grade 3 = 1) were used in each model.

First, the baseline hazard model is estimated, measuring student i's probability of reclassification in each time period j:

$$ln\left(\frac{h(t_{ij})}{1-h(t_{ij})}\right) = \beta_1 \alpha_j + \varepsilon_{\mathrm{ij}} \qquad (1)$$

α_j is a vector of time indicators for the number of years j after third grade that student i is observed in the data (where grade 3 equals time period 1). The vector of coefficients β_1 signify the hazard of being reclassified in each year t following third grade, given that the student was not yet reclassified by time t. Using these hazard estimates, the survivor function can be modeled, estimating the likelihood that the student will fail to be reclassified by time period *t:*

$$\hat{s}(t_j) = \hat{s}(t_{(j-1)})[1 - \hat{h}(t_j)] \qquad (2)$$

This function takes the product of the complement of the estimated hazard probability of reclassification for time period j, and the probability of survival from time period $j - 1$. In other words, to obtain the estimated probability of not being reclassified in three years, the model would multiply $[1 - h(t_1)] * [1 - h(t_2)] * [1 - h(t_3)]$, where each of the three terms represents the probability of not being reclassified in time periods $j = 1, 2,$ and 3, respectively. For ease of interpretation, the complement of the survivor function $(1 - \hat{s}(t_j))$, the cumulative failure function, is also reported (Motamedi et al., 2016; Thompson, 2017). This function calculates the cumulative probability that a student will experience reclassification by a given time period and *t*, and is a more applicable and interpretable metric.

$$\hat{c}(t_j) = 1 - \hat{s}(t_j)) \qquad (3)$$

Each of these metrics, the hazard, survival, and cumulative hazard are reported in the life table of student reclassification.

To estimate the relationship between teacher characteristics and ELs' hazard of reclassification, measures of teacher demographics are added to model (1), as well as controls for student and classroom characteristics:

$$ln\left(\frac{h(t_{ij})}{1-h(t_{ij})}\right) = \beta_1\alpha_j + \beta_2 D_{ij} + \ \beta_3 S_{ij} + \beta_4 C_{ij} + \ \varepsilon_{\mathrm{ij}} \qquad (4)$$

D_{ij} is a vector of teacher demographic characteristics of the mainstream reading teacher experienced by student i in time j, S_{ij} is a vector of student characteristics of student i in time j, and C_{ij} is a vector of classroom peer characteristics experienced by student i in time j. ε_{ij} represents the error-term, which captures any factors affecting students' time to reclassification not accounted for by the model. Standard errors are clustered at the student level to account for the intraclass correlations between students' annual records.

To estimate how different measures of teacher effectiveness are related to variation in ELs' rate of reclassification, each of the five measures of teacher effectiveness are added in turn:

$$ln\left(\frac{h(t_{ij})}{1-h(t_{ij})}\right) = \beta_1\alpha_j + \beta_2 D_{ij} + \ \beta_3 F_{ij} + \ \beta_4 S_{ij} + \beta_5 C_{ij} + \ \varepsilon_{\mathrm{ij}} \qquad (5)$$

F_{ij} represents a single measure of teacher effectiveness for the reading teacher assigned to student i in time j. Each measure of teacher effectiveness is added one at a time to examine the extent to which a given measure of teacher effectiveness may relate to ELs' hazard of reclassification, while accounting for other teacher demographic characteristics, and student and classroom characteristics.

Considerations for Discrete-Time Survival Analysis

Assumption of Proportionality

A key assumption for discrete-time survival analyses is the proportionality assumption, which holds that the relationship between a predictor and the hazard of reclassification is constant across all grade levels. If, for instance, a student's immigrant status was predictive of their hazard of reclassification, the proportionality assumption would hold that immigrant status has the same impact on student's reclassification hazard in all grades. However, it may be the case that the effect of a covariate on the reclassification hazard may be stronger or weaker across different grade levels (Box-Steffensmeier, 2004; Box-Steffensmeier et al., 2003).

To examine whether there are grounds to maintain the proportionality assumption, the estimated cumulative hazards as predicted by binary variables in the study were plotted along with the indicators for time. If the lines are parallel between the groups, it was concluded that the lines for both groups have the same slope and the proportional hazard assumption is not violated. If the lines for any covariates are not parallel, then this suggests that the proportional hazard assumption is not met, and an interaction term between that variable and time should be included in the model to allow for the relationship between the covariate and the hazard of reclassification to vary over time. The results of this examination showed that the lines for the estimated cumulative hazards for student retention, Black students, if the teacher was a person of color, years of experience, and SPED students were not parallel. However, when interactions between time and each covariate were added in the models, the variance inflation factors for the models increased, while the improvement in the model fit as measured by the log-likelihood, was not sufficient enough to justify the inclusion of the interactions. Furthermore, the inclusion of interaction terms made no meaningful changes to the estimated model coefficients. As such, interactions were not included in the models.

Assumptions Around Censoring

Concerns regarding left- and right-censored observations need to be addressed. Censored observations in survival analyses are observations for whom we do not know whether and when the event was experienced. Censoring may be non-informative or informative. When censoring is non-informative, such as when data collection ends and students are no longer observed, the mechanism for censorship is independent of the event occurrence. In this case, it can be assumed that the students censored were just as likely to experience the event as the students observed experiencing the event. However, when censoring is informative, the reason for missingness is not independent of the probability of event occurrence. If this is the case, it cannot be assumed that the censored observations are just as likely as those in the sample to experience the event. This type of censoring is informative of the students' hazard probability and may bias results.

The data analyzed here are right-censored. Right-censored data are students who are observed in the analytic sample, but do not experience the event during the window of observation, which in this study is grades 3-8. This may be because they never experience the event, because they exit the sample, i.e. leave the state's public school system, or because data collection ends. Survival analyses rely on the assumption that censoring is noninformative. This study attempts to lessen concerns of censoring by including in the analytic sample students who are consecutively observed and allows students who move between schools within the state to remain in the sample.

Left-censored data would be students who were reclassified prior to third grade. These students are individuals for whom the event was not observed (or included) in the analytic sample. Left-censored data are more problematic. While administrative data containing information on students' EL status from kindergarten onwards is available for all public-school students in the state, students in grades K-2 are not able to be linked to measures of teacher characteristics or student test scores. As the indicators of teacher effectiveness are key covariates of interest in the analysis, it was not possible to include students in grades K-2 in the analytic sample. Including students in the analysis who started school in the state anytime between kindergarten and third grade would be problematic because these data would be left censored. To the extent that students' prior school experiences (e.g. previous teachers, prior peers, early language ability, immigration to the U.S.) affected whether or they were reclassification by third grade or remained ELs, including these left-censored observations would be informative of their hazard of reclassification. To omit confounding variation, only students who started kindergarten in the state and did not move out of the state were included in the analytic sample.

Interpreting Results

Coefficients from the discrete-time survival analysis models are exponentiated to report odds ratios. Odds ratios greater than one indicate that a covariate is associated with an increased probability of reclassification and odds ratios less than one indicate that a covariate is associated with a decreased probability of reclassification. To interpret an odds ratio greater than one, a one unit increase in the covariate corresponds with a predicted increase in a students' hazard of reclassification in a given year by a factor of $100*(\exp(\beta) - 1)$. To interpret an odds ratio less than one, we calculate $\left(\frac{1}{\exp(\beta)} - 1\right) * 100$. This represents the increase in the probability of reclassification for students in the reference group.

Limitations

There are limitations to this study. First, since teachers' value-added scores are only available for teachers in grade 3 teachers and onwards, the analysis examines a unique cohort of EL students who enroll as ELs in kindergarten and are still ELs as of third grade. As such, this study is only able to speak to the relationship between teachers and students' hazard of reclassification for students after 3rd grade who had already been ELs in Tennessee since kindergarten. However, the availability of value-added scores nationwide is often limited to students is grades 3-8, as The No Child Left Behind Act of 2001, as well as its predecessor, the Every Student Succeeds Act of 2015, mandate standardized testing in reading and math for all students in grades 3-8.

Additionally, while data on the percent of a students' instructional time claimed by a teacher within a given subject are available, these data contain numerous reporting errors. As such, this study assumes that any link between students and teachers indicates that the student received instruction from the teacher. Finally, unlike data from other states (e.g. California) which allows researchers the ability to identify the type of language services received by students (i.e. dual-language, English immersion, etc.), the data in this study are limited in their ability to account for the effectiveness of ESL supports students receive, besides matching students to an ESL teacher and controlling for students' school district or district urbanicity.

Statement of Researcher Positionality

Prior to discussing preliminary findings, the author would like to make a brief note about researcher positionality in the context of this study. As a former elementary school teacher in Phoenix, Arizona, a large percentage of students in the school and classroom were current or former English Learners. These experiences working closely with reclassified EL students, as well as with colleagues teaching ESL or sheltered English immersion allowed the author to witness firsthand the complex instructional environment experienced by EL students, who often switched between teachers, programs, curricula, and peer groups. These experiences have shaped the author's understanding of EL students and created a commitment to researching policies to supporting ELs.

Results

Results from this analysis find that ELs assigned to mainstream reading teachers of color have greater years of experience are more likely to be reclassified in a given grade level. However, once predictors of teacher effectiveness are added, only teachers of color in the TVAAS sample are significantly associated with students' rate of reclassification, and significant relationships for teacher experience are not found in either sample. Instead, all five measures of teacher effectiveness tested—teacher TVAAS scores, TVAAS levels, average observation scores, observation quartiles, and overall level of effectiveness (LOE) scores—are positively and significantly associated with ELs hazard of reclassification. ELs assigned to an effect or highly effective teacher in reading, as measured by any of the measures, are more likely to experience reclassification in any given year. Once controls for students' classroom peers are added, these relationships continue to maintain. A series of robustness checks provide additional checks and verification for these findings.

Life Table of Analytic Sample

First, students' baseline hazard of reclassification is examined, providing an estimate for the instantaneous rate of change in the probability of reclassification in a specific year, conditional on the fact that that the student has not yet been reclassified. Table 1-6 presents the life table which shows the probability of reclassification for each year after third grade. Column 1 displays the number of years after third grade while column 2 displays the approximate grade for students. Column 3 displays the number of students who have yet to be classified at the start of the school year (students in the risk set), column 4 shows the number of students reclassified at the end of the school year, and column 5 shows the number of students that exited the sample (censored observations). Column 6 displays ELs' cumulative hazard of reclassification by that school year. Column 7 shows the probability of not being reclassified (survival), and column 8 shows the instantaneous probability of reclassification in each time period.

Of the 13,215 students who started as ELs in kindergarten, who are still ELs in third grade, and for whom student, teacher, and classroom data are available, 2,321 were reclassified, and 2,179 were censored. These students have a 17 percent likelihood of being reclassified at the end of third grade. For students remaining in risk set, their hazard of reclassification is about 50 percent after 3 years, or approximately in 5th grade. The instantaneous hazard rate is also the highest in this time period, at 32 percent. By the spring of 8th grade, 72 percent of students are likely to have been reclassified, 8 years after beginning as ELs in the state, as shown by the cumulative reclassification hazard. The hazard function remains fairly constant in middle school grades of 6-8, where students' instantaneous rate of reclassification ranges between 12 to 15 percent, as shown in Figure 1-2.

Life Table of Population

It should be noted that this table only shows reclassification for students who start as ELs in kindergarten and remain ELs until third grade. One concern may be that these students have a differential hazard of reclassification than that of all ELs in the state. To alleviate this concern, the instantaneous hazards of reclassification between the population of K-12 ELs in Tennessee from the 2005/06 through 2014/15 were compared to those in Table 1-6. As seen in rows 4-9 of the life table in Table 1-7 (representing Time 3-8), the hazards of reclassification between the K-12 EL population (column 6) and the sample of students represented by Table 1-6 (column 7) are relatively comparable. In grades 3-8, the approximate grades of students in the sample, the estimated hazards of reclassification in the sample are 4 to 9 percentage points higher than those in the full population. Given that the sample removes students from grades K-3 who were reclassified prior to grade 3 and removes students who were censored prior to third grade, this finding is expected. The students who remain in the state in the sample are less transitory. These students who continue to remain in the risk set may be more likely to be reclassified, creating a slight upward trend in the estimated hazard of reclassification in the sample. This may create some upwards bias in the estimates.

Discrete-Time Survival Analysis Results

Next, results from discrete-time multivariate models are presented. First, results from models estimating the relationship between teacher demographic characteristics and ELs hazard of reclassification are presented in Table 1-8. Results are presented for both the TVAAS and LOE samples. Exponentiated coefficients are presented as odds ratios.

Teacher Characteristics

When controlling for student characteristics and time, a ten year increase in teacher experience is associated with a 6 or 7 percent increase in students' hazard of reclassification in the LOE and TVAAS samples, respectively. Additionally, ELs assigned to a teacher of color are 12 percent more likely to be reclassified in any given year in the TVAAS sample. The coefficient on teacher of color is smaller and not significant in the LOE sample. With the addition of classroom controls, the relationship between teacher experience and student reclassification is no longer significant in both samples, while the coefficient on having a teacher of color remains significant and positive in the TVAAS sample. This suggests that, once characteristics of the students assigned to a teacher are accounted for, having a teacher of color is still predictive of the hazard of reclassification. Since this relationship is not present when the sample is expanded to include teachers who have an LOE score (over 6,000 of whom also have a TVAAS score), it suggests that the role of teacher race/ethnicity on EL reclassification may be particularly important for ELs' tested-area teachers.

Measures of Teacher Effectiveness

The second research question seeks to examine the relationship between measures of teacher effectiveness and variation in ELs' rate of reclassification. Once measures of teacher effectiveness are iteratively added, having a more experienced teacher or a teacher of color is less consistently associated with an increase in students hazard of reclassification. Table 1-9 displays results from models estimating the addition of measures of teacher effectiveness to the models shown in columns 1 of Table 1-8 above. A one unit increase in years of experience is only associated with a greater likelihood of reclassification in model 1, where teachers' lagged TVAAS score is controlled for. Similarly, having a teacher of color is only associated with a greater likelihood of reclassification when teachers' TVAAS or TVAAS level is accounted for. The relationship is not present when teacher observations, observation quartiles, or LOE scores are accounted for.

With respect to measures of teacher effectiveness, across all five models, a positive relationship between each measure of teacher effectiveness and a greater likelihood of reclassification is observed. For instance, compared to students with less effective teachers (those scoring 1 or 2) based on teachers' TVAAS level, students assigned to effective or highly effective teachers are 17 to 53 percent more likely to be reclassified. Similarly, as shown in Figure 1-3, students assigned to highly effective teachers based on teacher LOE are 27 percent more likely to be reclassified compared to students with less effective. Figure 1-4 illustrates how the cumulative likelihood reclassification for ELs assigned to teachers with different LOE scores is more disparate in grades 3-5, with the gap quickly closing in middle school grades 6-8.

ELs assigned to teachers scoring in the top three observation quartiles, or those assigned to higher performing teachers per the continuous TVAAS and continuous observation scores are also more likely to be reclassified. When the teacher observation score is broken down into quartiles, a significant, positive relationship between ELs assigned to teachers in the top three quartiles is observed. For example, ELs assigned to a teacher whose average observation score is in the top quartile of performance (with an average observation score between 4.23 – 5) are 47 percent more likely to be reclassified in a given year, compared to ELs assigned to a teacher in the lowest quartile (with an average observation score between 1 – 3.51). The addition of classroom controls, as shown in Table 1-10, reduces the effect size of teacher coefficients, but the significance of the coefficients on all measures of teacher effectiveness except the second observation quartile maintains across all models. This suggests that, while ELs' classroom characteristics may relate somewhat to ELs' likelihood of reclassification, measures of teacher effectiveness, and to some extent, having a teacher of color, are consistently positive and significant predictors.

Robustness and Sensitivity Checks

In order to try and further isolate the relationship between measures of teacher effectiveness and ELs' hazard of reclassification, four primary threats to internal validity are addressed, namely, (a) biased assignment of ELs to teachers, (b) varying sample sizes, (c) differences in resources for ELs across the state, and (d) model specification. In the section below, each threat to internal validity and the tests performed are discussed.

Biased Assignment of ELs to Teachers

Of primary concern is biased assignment of students to teachers. Is it the case that more effective teachers are better at teaching ELs? Or, could it be the case that more proficient ELs are more likely to be assigned to more effective teachers, making it appear as if they are more likely to be reclassified when they would have been reclassified regardless of the effectiveness of their reading teacher? Drawing data from ELs reading proficiency levels per the Tennessee Comprehensive Assessment Program (TCAP), the state's end of year summative assessment, the relationship between ELs' reading proficiency and teacher effectiveness is more closely scrutinized. The TCAP is administered to all public school students in grades 3-8. In addition to a continuous score, students are benchmarked as below basic proficiency, basic proficient, proficient, or advanced proficient using state-designated cutoff scores. To avoid concerns of endogeneity, students' prior year proficiency levels are used in the analysis.

As shown in Figure 1-5, 76.3 percent of ELs who are proficient or advanced proficient in reading based on their prior year reading TCAP score are assigned to a highly effective teachers based on teachers' overall level of effectiveness (LOE) in the prior year. In contrast, only 63.2 percent of students whose reading performance is below basic based are assigned to highly effective teachers. Results from logistic models predicting ELs' differential assignment to a highly effective teacher[9] shown in Table 1-11 demonstrate that, compared to ELs who are below

[9] A highly effective teacher was defined as one who scored in the topmost quartile per their prior year three-year composite value-added score or prior year average observation score, or as one who scored a 4 or 5 based on their prior year three-year composite value-added score or overall level of effectiveness score.

basic in reading proficiency, ELs who are basic proficient, proficient, or advanced proficient are significantly more likely to be assigned to a highly effective as measured by a teacher's prior year TVAAS level of effectiveness, observation score, or the teacher's overall LOE. To the extent that ELs who are proficient or highly proficient in reading are also more fluent in English, the finding from this test suggests that results from the main analysis may be upwardly biased, and that there is bias in the assignment of ELs to teachers based on EL performance and teacher effectiveness.

To account for this selection bias, models from the main analysis were re-estimated by adding a binary indicator for whether the EL is proficient/advanced proficient in reading based on their prior year TCAP score, as well as an indicator for whether the EL took the TCAP exam using an English Linguistically Simplified Assessment (ELSA). Once data on students' prior year TCAP scores is added, the sample is reduced by approximately 2,158 – 4,748 observations, as all grade 3 students and students with missing test score data are omitted. After controlling for ELs' prior year reading proficiency, the positive relationship between teacher effectiveness and ELs' likelihood of reclassification persisted for four of the five measures, though the effect sizes diminish, as shown in Table 1-12, columns "a". A student assigned to a highly effective teacher based on TVAAS level is 32 percent more likely to be reclassified than students assigned to a less effective teacher. Additionally, students assigned to teachers with a master's degree or higher are approximately 16 to 20 percent more likely to be reclassified than those assigned to those with a bachelor's or lower. However, ELs assigned to highly effective teachers based on teacher LOE score are no more or less likely to be reclassified compared to ELs assigned to less effective teachers. The addition of classroom controls, as shown in columns "b", illustrates that these significant, positive relationships persist, though effect sizes are further reduced. Moreover, the coefficient less than 1 on effective teachers suggests that ELs with effective teachers based on LOE score are less likely to be reclassified.

It is important to note that the reduction in the sample and the addition of new parameters capturing student performance increased the variance inflation factor (VIF) on the indicators for time. Estimates are sensitive to model specification. For instance, the coefficient on the indicator for ELs' reading proficiency is approximately 6 in the model with student covariates, suggesting that the estimate is overinflated and there is collinearity in the model. Since only five percent of students in the analytic sample with student TCAP scores are proficient or advanced proficient in reading in the prior year, models adding in a binary indicator for students who are basic proficient were also estimated. The addition of this third parameter further increased the VIF on the first indicator of time to higher than 10, which is commonly held as the maximum threshold at which the VIF should not exceed. The coefficient on the indicators for ELs' reading proficiency increased further, and the sign and significance on some measures of teacher effective changed. For the sake of parsimony, the simpler model was estimated, omitting the covariate for students who are basic proficient.

On the whole, accounting for biased assignment of more proficient ELs to highly effective teachers using ELs' prior year reading performance, it appears that a significant, positive relationship between measures of teacher effectiveness and ELs' hazard of reclassification continues to be observed. Given the sensitivity of the analysis using student test scores, likely due to the reduced sample and high volume of parameters, results from this analysis should be interpreted with caution.

Varying Sample Sizes

Overall level of effectiveness and observation scores are available for most teachers, while value-added scores are only available for tested area teachers, thereby limiting the sample size. Thus, a secondary concern is that the varying sample sizes across models may be including or excluding particular students from the model, thereby biasing results. To address this concern, models were re-estimated using a sample of students and teachers for whom all measures of teacher effectiveness were available (N=6,731). Controls were included for student and classroom characteristics. Results from this re-estimation, shown in Table 1-13, columns “a”, reveal qualitatively similar results as those in the main analysis. Assignment to a highly effective teachers across all measures is still positively and significantly associated with students’ hazard of reclassification. The addition of classroom covariates as shown in columns “b” somewhat diminishes the magnitude of these relationships, but not the significance, such that all measures of teacher effectiveness remain positively associated with EL reclassification, though the measure of teacher effectiveness based on teacher LOE is negatively associated with EL reclassification.

Finally, given the selection bias described above, models are estimated including controls for ELs’ language proficiency, as above. Classroom controls are included in models in column “b”. Results of this check, shown in Table 1-14 demonstrate that, even when limiting the analysis to a sample of teachers who have an effectiveness score for all five measures of teacher effectiveness and students who have prior year reading test score information, there still remains a positive and significant relationship between four of the five measures of teacher effectiveness and ELs likelihood of reclassification. However, there does not appear to be a significant, positive effect for effective teachers based on their TVAAS level and teachers with observations falling into the second and third quartiles.

The addition of classroom controls in column “b” diminishes the magnitude of these relationships, but again, their significance is maintained. Students assigned to teachers with a master’s degree or higher are also more likely to be reclassified in a given year. A negative effect is observed for students assigned to effective teachers based on their overall LOE score. This negative effect mirrors the negative effect on LOE score observed in the sensitivity check above. Again, these models are likely highly sensitive due to the reduced sample size and should be interpreted with caution.

Differences in EL Experiences Across Regions in the State

In examining within-state differences in students’ likelihood of reclassification in Texas, as well as differences in implementation of reclassification policy, Mavrogordato and White (2017) find that similar ELs in different parts of the state experience different hazards of reclassification. Interviews with practitioners revealed that differences may be explained by variation in the use of technology and data to make reclassification decisions, as well as variation in how reclassification policies were understood.

Similar within-state differences in ELs’ reclassification may be found in Tennessee, a state where ELs’ place of residence may vary depending on district, urbanicity, or region of the state. As such, dummy variables for district, district urbanicity[10], or CORE region[11] were added one at a time, along with classroom controls. Results shown in Tables 1-15, 1-16, and 1-17,

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[10] Data on district urbanicity were obtained from the National Center on Education Statistics (NCES). District urbanicity was classified as city, suburb, or town/rural community.

[11] Tennessee Centers of Regional Excellence, otherwise known as CORE regions, are geographic regions across the state. Each of the eight CORE regions are overseen by a CORE office to help provide differentiated support to schools in the region. In this analysis, the eight regions are collapsed into three, representing West, Middle, and East Tennessee.

respectively, show that, even when controlling for the district an EL is enrolled in, the urbanicity of the district, or the region within the state, ELs assigned to highly effective teachers on any of the five measures are more likely to be reclassified, such as highly effective teachers based on TVAAS and LOE levels, and teachers with observation scores in the top two quartiles.

Results from the addition of controls for students' proficiency in reading as well as classroom peers vary, as shown in Tables 1-18, 1-19, and 1-20. After adding district (Table 1-18) or core region fixed effects (Table 1-20), a positive relationship for the continuous and leveled measures for teachers' compositive value-added scores is observed, but no relationship is observed for observation or LOE scores. When fixed effects for urbanicity are included, a positive relationship for all measures except the overall LOE are observed (Table 1-19). Taken together, results suggest that, once students' schooling environment is considered, a positive, significant relationship between the measures of teacher effectiveness and ELs' hazard of reclassification is maintained.

Alternate Link Function

A final concern is the modeling strategy used. While the present analysis makes use of the logistic link for its ease of interpretability and familiarity, another popular choice is the complementary log-log (clog-log) link. The principal advantage of the clog-log link is its ability to provide estimates comparable to a continuous time hazard model by invoking a proportional hazards, rather than a proportional odds, assumption. Use of the clog-log link is useful if the presently discrete measure of time is believed to be continuous, where the event would occur in continuous time. Given that decisions around student reclassification occur at the end of each school year rather than continuously, the measure of time in this study is likely truly discrete. However, since recent work on EL reclassification has made use of the clog-log link function (e.g. Mavrogordato and White, 2017), the main models in Tables 1-10 and the models including the TCAP scores, shown in Table 1-12, were re-estimated using the clog-log link function. Results of this re-estimation, shown in Tables 1-21 and 1-22, respectively, illustrate how use of the clog-log link function produces results that are qualitatively similar to those estimated using the logit link function, though the log likelihood of the models using the clog-log link are slightly more negative, suggesting worse model fit.

Discussion

The purpose of this study is to determine how characteristics of ELs' mainstream classroom teachers and which measures of teacher effectiveness predict ELs' rate of reclassification. Using a discrete-time survival analysis approach, which allows for the estimation of ELs' instantaneous rate of reclassification in each grade from grade 3 onwards, this study finds some evidence that ELs assigned to mainstream classroom teachers of color are more likely to be reclassified within a given year. While a small positive relationship between the number of years of experience and ELs' rate of reclassification is also observed, the relationship disappears once measures of teacher effectiveness is controlled for.

This finding suggests that mainstream teacher race/ethnicity may play a role in ELs' experiences in a reading classroom. Numerous studies examining the role of student-teacher race-congruence on student outcomes suggest two potential mechanisms through which teacher race/ethnicity may improve student learning: (a) active effects, in which a teacher's race may help the teacher better connect with and provide culturally responsive instruction for students, and (b) passive effects, in which alignment between student and teacher race may diminish students' stereotype threat (Egalite & Kisida, 2017; Gershenson, 2016; Joshi et al., 2018). It may also be that case that teachers of color are more likely to approach ELs' language development with asset-based thinking and be more likely to reclassify students with a composite score of 4 on the ELDA exam.[12] This finding corresponds with findings from Loeb et al. (2014) who find that teachers fluent in EL students' home language or those with a bilingual teaching certification are more effective with their EL students than their non-EL students. These indicators similarly demonstrate a positive effect from an alignment between teachers' ability to produce culturally responsive instruction and students' academic performance in reading and math.

However, all five measures of teacher effectiveness consistently predict ELs' rate of reclassification, and findings persist once classroom controls are included in models. ELs assigned to highly effective or effective teachers, as measured by teachers' prior year TVAAS levels in reading are 17 to 53 percent more likely to be reclassified in a given year compared to ELs assigned to a less effective teacher. Yet, there exists evidence of biased assignment of ELs to mainstream reading teachers based on teachers' level of effectiveness, with ELs who are more fluent in reading more likely to be assigned to highly effective teachers. A series of robustness checks attempts to account for this selection bias by controlling for ELs' prior year performance in reading using Tennessee's standardized test scores.

Results from four robustness and sensitivity checks accounting for students' prior year test scores, varying sample size, regional location, and log-link specification supports findings from the main analysis, though it should be noted that results are sensitive to the diminished sample size and to the inclusion of additional covariates. Robustness checks adding in controls for students' prior year test score maintain the findings from the main analysis, though effective

[12] Students with a composite score of 4 may be reclassified, while students with a composite score of 5 must be reclassified. The names of students with a composite score of 4 who are not reclassified must be submitted to the state, along with a reason for not reclassifying the students (*Overview of Title III English as a Second Language: Service Requirements for Non-English Background Students*, 2013).

teachers and teachers in the second and third observation quartiles are no longer predicted to improve students' likelihood of reclassification. The significant coefficients observed here previously may have been due to the selection bias in student assignment. Nevertheless, models controlling for student performance still find that ELs assigned to highly effective teachers based on TVAAS and observations are more likely to be reclassified.

The strategic assignment of ELs to effective mainstream teachers is a critical finding of this study. Even when making a conservative estimate, ELs are anywhere from 20 to 30 percent more likely to be reclassified when assigned to a highly effective teacher. As the sample of students focuses on students who have already been ELs in the state for three years prior to third grade, school leaders and policymakers may consider assigning ELs to highly effective teachers in year four onwards to support their language development. While effective teachers are a finite resource, they do comprise a substantial part of the teaching force. As school leaders and policymakers serve as gatekeepers to ELs access to resources and policies around EL reclassification, it is important to consider access to effective teachers as a resource for ELs' language learning (Mavrogordato & White, 2020; White & Mavrogordato, 2019). Schools may strategically place highly effective teachers with ELs at points critical for EL development, such as in their fourth or fifth year as an EL, as students are categorized as long-term ELs (LTELs) after classification as an EL for 6 or more years. Furthermore, the disparity in assignment of ELs to highly effective teachers may also be ameliorated through more equitable assignment practices and improved professional development for all teachers on how to effectively differentiate instruction and integrate various instructional strategies for ELs.

Why might highly effective teachers be more effective at improving ELs' likelihood of reclassification? These teachers may be more skilled at differentiated instruction that helps students build language skills or using practices to build language proficiency in EL students (Bunch, 2013). Differentiated instruction for ELs is distinct from differentiation for non-EL students because ELs are simultaneously learning language, content, and culture. While mainstream teachers may differentiate instruction for students of different levels of academic proficiency by changing the difficulty level of the content, differentiation of instruction using techniques appropriate for ELs, may not always be implemented. As noted by guidance for EL learning by the Institution of Education Sciences (2007) as well as numerous scholars of EL learning, teachers of ELs should provide students explicit instruction on vocabular, phonics, and academic language, incorporate small-group instruction, and scaffold learning through the use of visuals, comprehensible input, and language support tools such as simplified texts or technology (August & Shanahan, 2006; Bunch, 2013; Calderón et al., 2011; Darling-Aduana & Heinrich, 2018; Goldenberg, 2008; Lucas et al., 2008; Solomon et al., 2006). As Bunch (2013) writes, preparing teachers to work with ELs "requires development of *pedagogical language knowledge"*, i.e. knowledge of language related to the discipline and contexts of teaching and learning (p. 307). Implementing these techniques in a classroom would require considerable planning, skill, and intentionality.

It is also significant that all five measures predict student reclassification, some with more or less consistency, since the measures are not highly correlated. It is especially interesting that the measures of teacher value-added and observation score, which have a low correlation of 0.26 (and likely measure different components of a teacher's instruction), both predict the likelihood of EL reclassification. This suggests that, while measures may pick up different constructs, each is able to pick up teacher behaviors that improves EL's language development.

Since all measures of teacher effectiveness predict ELs' rate of reclassification, is there a measure that stands out for use in decision-making? No single measure is ideal; practitioners may choose to select based on their context-specific needs. While teachers' overall LOE is available for more teachers, the measure appears sensitive to the inclusion of student proficiency covariates and decreases in sample size. Teacher value-added and average observation scores consistently predict EL's hazard of reclassification, but the latter are only available for tested-area teachers. The unavailability of the TVAAS metric for non-tested area may not be as pressing a concern, since relatively few teachers had an observation score but no TVAAS score. Using average observation score quartiles could be a helpful metric for practitioners, as it is easy to understand. Nevertheless, in Tennessee, practitioners have a range of measures readily available to identify effective teachers to whom ELs may be assigned.

Conclusion

This study is among the first to examine the role teacher characteristics may play in EL students' rate to reclassification, making an important contribution to the growing body of literature on ELs. Second, while prior studies examining EL students' time to reclassification and characteristics associated with their reclassification have used data from large, urban areas populated with large numbers of EL students, such as California, Texas, and New York. However, these contexts are atypical of the learning environments of many ELs in the country who are living in more suburban or rural towns. In examining the nature of EL reclassification in a state that has a smaller, yet growing, body of EL students, the findings of this study may be more generalizable to the average EL in the country.

For ELs who have not yet attained English proficiency by 3rd grade, despite having attending U.S. schools since kindergarten, assignment to highly effective teachers in upper elementary and middle grades may be a lever to help students attain English proficiency sooner. Doing so may maximize the number of EL students who are able to be reclassified, a status change that has been found to improve numerous outcomes for ELs (Callahan, 2005; Callahan et al., 2009; Callahan & Shifrer, 2016; Carlson & Knowles, 2016; Johnson, 2019; Pope, 2016). Furthermore, strategic assignment to highly effective teachers could be a way to prevent ELs from becoming long-term ELs (LTELs), a classification used for students who have been English Learners for 6 or more years. Given that LTELs have limited literacy in English, struggle in all subject areas, and may be tracked into lower-level classes (Callahan, 2005; Menken & Kleyn, 2010), assignment to highly effective teachers could improve outcomes for ELs who are at risk of not attaining proficiency in English. Additionally, parallel to findings from prior work on teacher preparation, this study further underscores the need for training and professional development for mainstream classroom teachers on strategies to work with ELs, as well as the need for greater opportunities for mainstream and ESL teachers to collaborate together to support their students (Darling-Aduana & Heinrich, 2018; Karabenick & Noda, 2004; Pettit, 2011).

Since highly effective teachers are a finite resource, future work is encouraged to examine whether there are critical grades in which assignment to an effective reading teacher may maximize ELs likelihood of reclassification and whether the number of years that an EL is assigned to an effective teacher relates to how long it takes ELs to be reclassified. Future work is also encouraged to examine how mainstream teacher characteristics affect ELs rate of reclassification in early grades and to examine differences in EL' rate of reclassification depending on the proportion of time spent with an ESL teacher versus a mainstream teacher in reading.

References

August, D., & Shanahan, T. (Eds.). (2006). *Developing Literacy in Second-Language Learners: Report of the National Literacy Panel on Language-Minority Children and Youth* (1 edition). Routledge.

Ballou, D., & Springer, M. G. (2015). Using Student Test Scores to Measure Teacher Performance: Some Problems in the Design and Implementation of Evaluation Systems. *Education Researcher*, *44*(2), 77–86.

Borman, G. D., & Kimball, S. M. (2005). Teacher Quality and Educational Equality: Do Teachers with Higher Standards-Based Evaluation Ratings Close Student Achievement Gaps? *The Elementary School Journal*, *106*(1), 3–20. https://doi.org/10.1086/496904

Box-Steffensmeier, J. M. (2004). *Event History Modeling: A Guide for Social Scientists*. Cambridge University Press.

Box-Steffensmeier, J. M., Reiter, D., & Zorn, C. (2003). Nonproportional Hazards and Event History Analysis in International Relations. *Journal of Conflict Resolution*, *47*(1), 33–53. https://doi.org/10.1177/0022002702239510

Boyd, D. J., Grossman, P. L., Lankford, H., Loeb, S., & Wyckoff, J. (2009). Teacher Preparation and Student Achievement. *Educational Evaluation and Policy Analysis*, *31*(4), 416–440. https://doi.org/10.3102/0162373709353129

Bunch, G. C. (2013). Pedagogical Language Knowledge: Preparing Mainstream Teachers for English Learners in the New Standards Era. *Review of Research in Education*, *37*(1), 298–341. https://doi.org/10.3102/0091732X12461772

Calderón, M., Slavin, R., & Sánchez, M. (2011). Effective Instruction for English Learners. *The Future of Children*, *21*(1), 103–127. JSTOR.

Callahan, R. M. (2005). Tracking and high school English learners: Limiting opportunity to learn. *American Educational Research Journal*, *42*(2), 305–328.

Callahan, R. M., & Shifrer, D. (2016). Equitable access for secondary English learner students: Course taking as evidence of EL program effectiveness. *Educational Administration Quarterly*, *52*(3), 463–496.

Callahan, R. M., Wilkinson, L., Muller, C., & Frisco, M. (2009). ESL Placement and Schools: Effects on Immigrant Achievement. *Educational Policy*, *23*(2), 355–384. https://doi.org/10.1177/0895904807310034

Carlson, D., & Knowles, J. E. (2016). The Effect of English Language Learner Reclassification on Student ACT Scores, High School Graduation, and Postsecondary Enrollment: Regression Discontinuity Evidence from Wisconsin. *Journal of Policy Analysis & Management*, *35*(3), 559–586. https://doi.org/10.1002/pam.21908

Cirino, P. T., Pollard-Durodola, S. D., Foorman, B. R., Carlson, C. D., & Francis, D. J. (2007). Teacher Characteristics, Classroom Instruction, and Student Literacy and Language Outcomes in Bilingual Kindergartners. *The Elementary School Journal*, *107*(4), 341–364. https://doi.org/10.1086/516668

Clotfelter, C. T., Ladd, H. F., & Vigdor, J. L. (2007). *How and why do teacher credentials matter for student achievement?* (pp. 1–56). National Center for Analysis of Longitudinal Data in Education Research.

Clotfelter, C. T., Ladd, H. F., & Vigdor, J. L. (2010). Teacher Credentials and Student Achievement in High School A Cross-Subject Analysis with Student Fixed Effects. *Journal of Human Resources*, *45*(3), 655–681. https://doi.org/10.3368/jhr.45.3.655

Cohen, J., & Goldhaber, D. (2016). Building a More Complete Understanding of Teacher Evaluation Using Classroom Observations. *Educational Researcher*, *45*(6), 378–387.

Commission on Teacher Credentialing. (2018). *English Learner Authorization*. California Department of Education. https://www.ctc.ca.gov/educator-prep/ela

Commission on Teacher Credentialing. (2019). *Serving English Learners*. California Department of Education. https://www.ctc.ca.gov/docs/default-source/leaflets/cl622.pdf?sfvrsn=c1862043_8

Dabach, D. B. (2015). Teacher Placement Into Immigrant English Learner Classrooms: Limiting Access in Comprehensive High Schools. *American Educational Research Journal*, *52*(2), 243–274. https://doi.org/10.3102/0002831215574725

Darling-Aduana, J., & Heinrich, C. J. (2018). The role of teacher capacity and instructional practice in the integration of educational technology for emergent bilingual students. *Computers & Education*, *126*, 417–432. https://doi.org/10.1016/j.compedu.2018.08.002

Darling-Hammond, L. (2000). Teacher Quality and Student Achievement. *Education Policy Analysis Archives*, *8*(0), 1. https://doi.org/10.14507/epaa.v8n1.2000

Darling-Hammond, L., Amrein-Beardsley, A., Haertel, E. H., & Rothstein, J. (2011). *Getting Teacher Evaluation Right: A Background Paper for Policy Makers* (p. 14). American Educational Research Association and the National Academy of Education.

de Jong, E. J., Harper, C. A., & Coady, M. R. (2013). Enhanced Knowledge and Skills for Elementary Mainstream Teachers of English Language Learners. *Theory Into Practice*, *52*(2), 89–97. https://doi.org/10.1080/00405841.2013.770326

Egalite, A. J., & Kisida, B. (2017). The effects of teacher match on students' academic perceptions and attitudes. *Educational Evaluation and Policy Analysis*, 0162373717714056.

Ehrenberg, R. G., & Brewer, D. J. (1995). Did Teachers' Verbal Ability and Race matter in the 1960s? Coleman Revisited. *Economics of Education Review*, *14*(1), 1–21.

Esch, C. E., Chang-Ross, C. M., Guha, R., Humphrey, D. C., Shields, P. M., Tiffany-Morales, J. D., Wechsler, M. E., & Woodworth, K. R. (2005). *The Status of the Teaching Profession*. The Center for the Future of Teaching and Learning. https://files-eric-ed-gov.proxy.library.vanderbilt.edu/fulltext/ED491141.pdf

Every Student Succeeds Act, 20 U.S.C. § 6301 (2015). https://www.congress.gov/bill/114th-congress/senate-bill/1177

Gándara, P., Rumberger, R., Maxwell-Jolly, J., & Callahan, R. M. (2003). English Learners in California Schools: Unequal resources, 'Unequal outcomes. *Education Policy Analysis Archives*, *11*(0), 36. https://doi.org/10.14507/epaa.v11n36.2003

Garrett, R., Davis, E., & Eisner, R. (2019). *Student and school characteristics associated with academic performance and English language proficiency among English learner students in grades 3–8 in the Cleveland Metropolitan School District* (Regional Educational Laboratory: Midwest, pp. 1–55). American Institutes for Research.

Garrett, R., & Steinberg, M. (2015). Examining teacher effectiveness using classroom observation scores: Evidence from the randomization of teachers to students. *Educational Evaluation and Policy Analysis*, *37*, 224–242.

Gershenson, S. (2016). Linking Teacher Quality, Student Attendance, and Student Achievement. *Education Finance and Policy*, *11*(2), 125–149. https://doi.org/10.1162/EDFP_a_00180

Goldenberg, C. (2008). Teaching English Language Learners: What the research does—And does not—Say. *American Educator*, *Summer*, 1–19.

Goldhaber, D., & Hansen, M. (2013). Is it Just a Bad Class? Assessing the Long-term Stability of Estimated Teacher Performance. *Economica, 80*(319), 589–612. https://doi.org/10.1111/ecca.12002

Guarino, C. M., Reckase, M. D., & Wooldridge, J. M. (2015). Can Value-Added Measures of Teacher Performance Be Trusted? *Education Finance and Policy*, *10*(1), 117–156. https://doi.org/10.1162/EDFP_a_00153

Hakuta, K., & Pecheone, R. (2016). Supporting English Learners and treating bilingualism as an asset. In M. Hansen & J. Valant (Eds.), *Memos to the President on the Future of U.S. Education Policy*. Brookings Institution. https://dpi.wi.gov/sites/default/files/imce/esea/pdf/bul_0801.pdf

Hanushek, E. A. (1992). The Trade-off between Child Quantity and Quality. *Journal of Political Economy*, *100*(1), 84–117. https://doi.org/10.1086/261808

Harper, C. A., de Jong, E. J., & Platt, E. J. (2008). Marginalizing English as a second language teacher expertise: The exclusionary consequences of No Child Left Behind. *Language Policy*, *7*(3), 268–284.

Hunter, S. (2018). *History of TEAM Teacher Evaluation Policy* (pp. 1–98). Tennessee Education Research Alliance.

Johnson, A. (2019). The Effects of English Learner Classification on High School Graduation and College Attendance. *AERA Open*, *5*(2), 233285841985080. https://doi.org/10.1177/2332858419850801

Joshi, E., Doan, S., & Springer, M. G. (2018). Student-Teacher Race Congruence: New Evidence and Insight From Tennessee: *AERA Open*. https://doi.org/10.1177/2332858418817528

Karabenick, S. A., & Noda, P. A. C. (2004). Professional Development Implications of Teachers' Beliefs and Attitudes Toward English Language Learners. *Bilingual Research Journal*, *28*(1), 55–75. https://doi.org/10.1080/15235882.2004.10162612

Loeb, S., Soland, J., & Fox, L. (2014). Is a good teacher a good teacher for all? Comparing value-added of teachers with their English learners and non-English learners. *Educational Evaluation and Policy Analysis*, *36*(4), 457–475.

López, F., Scanlan, M., & Gundrum, B. (2013). Preparing Teachers of English Language Learners: Empirical Evidence and Policy Implications. *Education Policy Analysis Archives*, *21*, 20. https://doi.org/10.14507/epaa.v21n20.2013

Lucas, T. (2011). Language, schooling, and the preparation of teachers for linguistic diversity. In T. Lucas (Ed.), *Teacher preparation for linguistically diverse classrooms: A resource for teacher educators* (pp. 3–17). Routledge.

Lucas, T., & Grinberg, J. (2008). Responding to the linguistic reality of mainstream classrooms: Preparing all teachers to teach English language learners. In M. Cochran-Smith, S. Feiman-Nemser, & J. McIntyre (Eds.), *Handbook of research on teacher education: Enduring issues in changing contexts* (3rd ed., pp. 606–636). Lawrence Erlbaum Associates.

Lucas, T., & Villegas, A. M. (2010). The Missing Piece in Teacher Education: The Preparation of Linguistically Responsive Teachers. *National Society for the Study of Education*, *109*(2), 297–318.

Lucas, T., Villegas, A. M., & Freedson-Gonzalez, M. (2008). Linguistically Responsive Teacher Education: Preparing Classroom Teachers to Teach English Language Learners. *Journal of Teacher Education*, *59*(4), 361–373. https://doi.org/10.1177/0022487108322110

Master, B., Loeb, S., Whitney, C., & Wyckoff, J. (2016). Different Skills?: Identifying Differentially Effective Teachers of English Language Learners. *The Elementary School Journal*, *117*(2), 261–284. https://doi.org/10.1086/688871

Mavrogordato, M., & White, R. (2017). Reclassification Variation: How Policy Implementation Guides the Process of Exiting Students From English Learner Status. *Educational Evaluation and Policy Analysis*, *39*(2), 281–310.

Mavrogordato, M., & White, R. S. (2020). Leveraging Policy Implementation for Social Justice: How School Leaders Shape Educational Opportunity When Implementing Policy for English Learners. *Educational Administration Quarterly*, *56*(1), 3–45. https://doi.org/10.1177/0013161X18821364

Menken, K., & Kleyn, T. (2010). The long-term impact of subtractive schooling in the educational experiences of secondary English language learners. *International Journal of Bilingual Education and Bilingualism*, *13*(4), 399–417. https://doi.org/10.1080/13670050903370143

Motamedi, J. G., Singh, M., & Thompson, K. D. (2016). *English learner student characteristics and time to reclassification: An example from Washington state*.

National Center for Education Statistics. (2020). *English Language Learners in Public Schools*. Institute of Education Sciences (IES). https://nces.ed.gov/programs/coe/indicator_cgf.asp#:~:text=The%20percentage%20of%20public%20school,%2C%20or%203.8%20million%20students).

Nye, B., Konstantopoulos, S., & Hedges, L. V. (2004). How Large are Teacher Effects? *Educational Evaluation and Policy Analysis*, *26*(3), 237–257.

Office of English Language Acquisition Services. (2020). *SEI Endorsement*. Arizona Department of Education. https://www.azed.gov/oelas/sei-endorsement/

Overview of Title III English as a Second Language: Service Requirements for Non-English Background Students. (2013). Tennessee Department of Education. https://eplan.tn.gov/documentlibrary/ViewDocument.aspx?DocumentKey=21839&inline=true

Pettit, S. K. (2011). Teachers' Beliefs About English Language Learners in the Mainstream Classroom: A Review of the Literature. *International Multilingual Research Journal*, *5*(2), 123–147. https://doi.org/10.1080/19313152.2011.594357

Phillips, K. J. R. (2010). What Does "Highly Qualified" Mean for Student Achievement? Evaluating the Relationships between Teacher Quality Indicators and At-Risk Students' Mathematics and Reading Achievement Gains in First Grade. *The Elementary School Journal*, *110*(4), 464–493. https://doi.org/10.1086/651192

Pope, N. G. (2016). The Marginal effect of K-12 English language development programs: Evidence from Los Angeles Schools. *Economics of Education Review*, *53*, 311–328. https://doi.org/10.1016/j.econedurev.2016.04.009

Quintero, D., & Hansen, M. (2017, June 2). English learners and the growing need for qualified teachers. *Brookings*. https://www.brookings.edu/blog/brown-center-chalkboard/2017/06/02/english-learners-and-the-growing-need-for-qualified-teachers/

Rivkin, S. G., Hanushek, E. A., & Kain, J. F. (2005). Teachers, Schools, and Academic Achievement. *Econometrica*, *73*(2), 417–458.

Rockoff, J. E. (2004). The Impact of Individual Teachers on Student Achievement: Evidence from Panel Data. *The American Economic Review*, *94*(2), 247–252.

Rockoff, J. E., Jacob, B. A., Kane, T. J., & Staiger, D. O. (2011). Can you recognize an effective teacher when you recruit one? *Education*, *6*(1), 43–74.

Ruiz Soto, A. G., Hooker, S., & J. Batalova. (2015). *States and Districts with the Highest Number and Share of English Language Learners* (ELL Information Center Fact Sheet Series, pp. 1–4). Migration Policy Institute.

Rumberger, R. W. (2003). *One Quarter of California's Teachers for English Learners Not Fully Certified* (No. 3; EL Facts, p. 2). University of California Linguistic Minority Research Institute.

Schools and Staffing Survey 2011-12. (2012). Number of Public School Teachers and Percentage of Public School Teachers Who Taught Limited-English Proficiency (LEP) or English-Language Learner (ELL) Students, by Selected School and Teacher Characteristics: 2011–12. https://nces.ed.gov/surveys/sass/tables/sass1112_498_t1n.asp

Singer, J. D., & Willett, J. B. (2003). *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence* (1st Edition). Oxford University Press.

Slama, R. B. (2012). A longitudinal analysis of academic English proficiency outcomes for adolescent English language learners in the United States. *Journal of Educational Psychology*, *104*(2), 265–285. https://doi.org/10.1037/a0025861

Solomon, M., Lalas, J., & Franklin, C. (2006). Making Instructional Adaptations for English Learners in the Mainstream Classroom: Is It Good Enough? *Multicultural Education; San Francisco*, *13*(3), 42–45.

Steinberg, M., & Garrett, R. (2016). Classroom Composition and Measured Teacher Performance: What Do Teacher Observation Scores Really Measure? *Educational Evaluation and Policy Analysis*, *38*(2), 293–317. https://doi.org/10.3102/0162373715616249

Stronge, J. H., Ward, T. J., & Grant, L. W. (2011). What Makes Good Teachers Good? A Cross-Case Analysis of the Connection Between Teacher Effectiveness and Student Achievement. *Journal of Teacher Education*, *62*(4), 339–355. https://doi.org/10.1177/0022487111404241

Taylor, J., Roehrig, A. D., Hensler, B. S., Connor, C. M., & Schatschneider, C. (2010). Teacher Quality Moderates the Genetic Effects on Early Reading. *Science*, *328*(5977), 512–514. https://doi.org/10.1126/science.1186149

Tennessee Department of Education. (2013). *Overview of TVAAS Composites for Teachers in Tested Subjects*. Tennessee Department of Education.

Tennessee Department of Education. (2016). *English as a Second Language Program Guide in TN* (pp. 1–121). Tennessee Department of Education. https://www.tn.gov/assets/entities/education/attachments/esl_english_as_a__second_language_program_guide.pdf

Tennessee Department of Education. (2018). *English as a Second Language Manual* (pp. 1–87). https://4.files.edl.io/67f0/09/20/18/134404-31b55b25-a392-4dc3-b12a-b5b056b308c9.pdf

Thompson, K. (2017). English Learners' Time to Reclassification: An Analysis. *Educational Policy*, *31*(3), 330–363.

Umansky, I. M., & Reardon, S. F. (2014). Reclassification Patterns among Latino English Learner Students in Bilingual, Dual Immersion, and English Immersion Classrooms.

American Educational Research Journal, *51*(5), 879–912. https://doi.org/10.3102/0002831214545110

U.S. Department of Education. (2016). *Tools and Resources for Identifying All English Learnerss*. Office of English Language Acquisition. https://www2.ed.gov/about/offices/list/oela/english-learner-toolkit/chap1.pdf

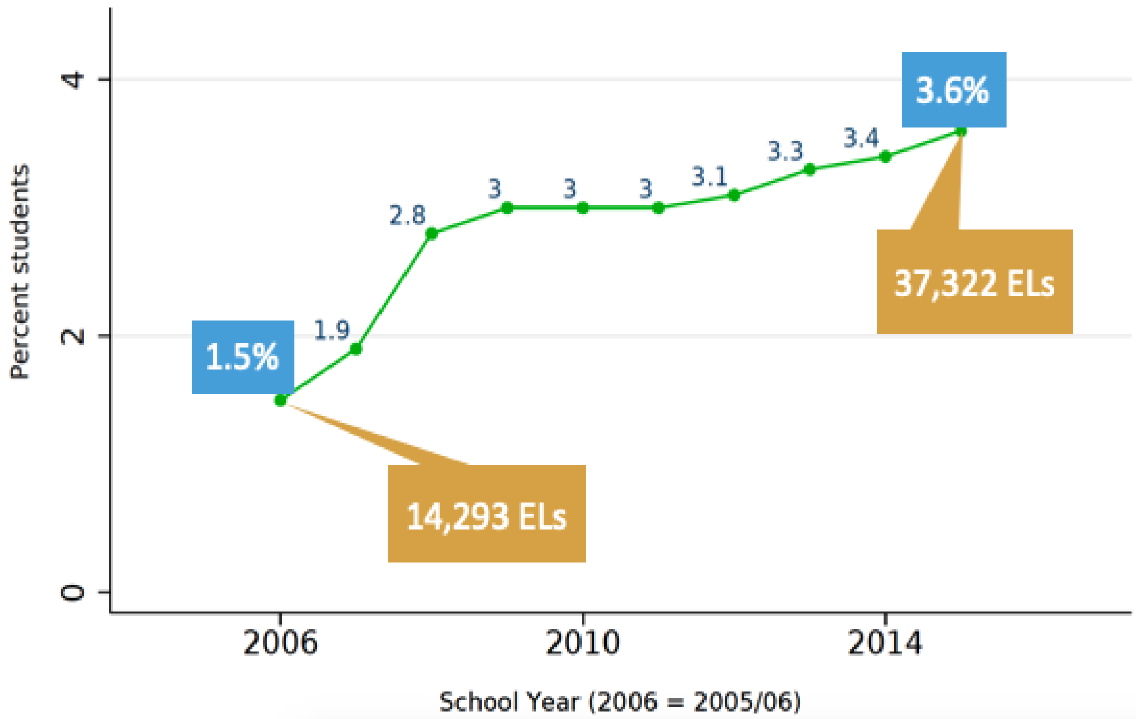
Wayne, A. J., & Youngs, P. (2003). Teacher Characteristics and Student Achievement Gains: A Review. *Review of Educational Research*, *73*(1), 89–122. https://doi.org/10.3102/00346543073001089

White, R. S., & Mavrogordato, M. (2019). Educators' Use of Policy Resources to Understand English-Learner Policies. *Leadership and Policy in Schools*, *18*(4), 560–590. https://doi.org/10.1080/15700763.2018.1513150

Zehler, A. M., Fleischman, H. L., Hopstock, P. J., Stephenson, T. G., Pendzick, M. L., & Sapru, S. (2003). *Policy Report: Summary of Findings Related to LEP and SPED-LEP Students—Submitted to U.S. Department of Education, Office of English Language Acquisition, Language Enhancement, and Academic Achievement of Limited English Proficient Students (OELA).* (ED-00-CO-0089; Descriptive Study of Services to Limited English Proficient (LEP) Students and LEP Students with Disabilities, p. 58). Development Associates, Inc.

Tables and Figures

Figure 1- 1:Percent English Learners in Tennessee Public Schools Over Time



Note: Population of English Learners (ELs) drawn from ELs enrolled in grades K-12 in Tennessee between the 2006/07 through 2014/15 school years. Percent students who are ELs calculated as the number of ELs out of the total number of students enrolled in a given school year. Data come from the Tennessee Education Research Alliance (TERA), a research-practice partnership between the Tennessee Department of Education and Vanderbilt University's Peabody College of Education.

Table 1- 1 Correlation Matrix of Measures of Teacher Effectiveness in Main Analytic Sample

	(1)	(2)	(3)
(1) Mean 3-Year TVAAS Index Composite (t-1)	1		
(2) Mean Observation Score (t-1)	0.26	1	
(3) Overall Level of Effectiveness (LOE)	0.65	0.53	1

Note: Table shows correlations between lagged (t-1) measures of the (1) continuous 3-year TVAAS index composite, (2) mean observation score, and (3) overall level of effectiveness (LOE) in the main analytic sample of teachers with available 3-year TVAAS index composite scores (N = 7,497). Correlations amongst these measures in the full sample were comparable to those in Table 1-1. In the full sample, the correlation between the 3-year TVAAS index composite and the mean observation score is 0.33, between the 3-year TVAAS index composite and LOE score is 0.64, and between the observation and LOE scores is 0.51 (N=62,395).

Table 1- 2 Number of Students per Cohort, by Sample

Panel A: Sample with Available Lagged TVAAS 3-Year Index Composite Scores

	Years After Grade 3						
Cohort	0 (~Grade 3)	1	2	3	4	5 (~Grade 8)	Total
2009	0	0	0	0	43	34	77
2010	0	0	1	131	106	110	348
2011	0	0	501	225	213	0	939
2012	0	747	562	303	0	0	1,612
2013	123	1,042	651	0	0	0	1,816
2014	914	1,094	0	0	0	0	2,008
2015	697	0	0	0	0	0	697
N Observations	1,734	2,883	1,715	659	362	144	7,497

Panel B: Sample with Available Lagged LOE and Observation Scores

	Years After Grade 3						
Cohort	0 (~Grade 3)	1	2	3	4	5 (~Grade 8)	Total
2009	0	0	0	0	43	35	78
2010	0	0	1	129	91	87	308
2011	0	0	510	226	166	0	902
2012	0	853	548	262	0	0	1,663
2013	1,196	1,087	562	0	0	0	2,845
2014	1,498	1,189	0	0	0	0	2,687
2015	1,706	0	0	0	0	0	1,706
N Observations	4,400	3,129	1621	617	300	122	10,189

Note: Each row represents a cohort. Cohorts are measured as the year a student first started grade 3. So, students in the 2009 cohort were in grade 3 in 2009 and were in grade 8 in 2014. Each column represents the number of years after grade 3. Column "0" is grade 3 and column "5" is 5 years following grade 3 (approximately grade 8 for most students). The value in each cell represents the number of students from a given cohort who are in the sample after a certain number of years after grade 3. Panel A shows the sample distribution for the TVAAS sample while Panel B shows the sample distribution for the LOE sample.

Table 1- 3 Mean Characteristics for Analytic Samples (TVAAS and LOE Samples)

	TVAAS Composite Sample	LOE Composite Sample
Time		
0 Years (~Gr3)	23.13%	43.18%
1 Year (~Gr4)	38.46%	30.71%
2 Years (~Gr5)	22.88%	15.91%
3 Years (~Gr6)	8.79%	6.06%
4 Years (~Gr7)	4.83%	2.94%
5 Years (~Gr8)	1.92%	1.20%
Cohort 2009	1.03%	0.77%
Cohort 2010	4.64%	3.02%
Cohort 2011	12.53%	8.85%
Cohort 2012	21.50%	16.32%
Cohort 2013	24.22%	27.92%
Cohort 2014	26.78%	26.37%
Cohort 2015	9.3%	16.7%
Student Characteristics		
FRPL	92.64%	92.64%
Special Education	15.11%	13.82%
Female	44.50%	44.35%
Immigrant	13.17%	13.49%
Asian/Other	5.68%	5.69%
Black	3.08%	3.08%
Latinx	87.81%	86.10%
White	3.43%	5.12%
Retained	0.45%	0.39%
Teacher Characteristics		
Logged Salary	$10.79	$10.80
Female	94.05%	94.70%
Age	41	41
Years of Experience	10	10
Asian/Other	0.48%	0.63%
Black	29.05%	26.66%
Latinx	0.23%	0.20%
White	70.24%	72.52%
Teacher of Color	29.76%	27.48%
Masters or Higher	60.70%	60.87%
Both Mainstream and ESL Teachers	35.45%	33.96%

Classroom Peer Characteristics		
Percent FRPL	76.96%	77.46%
Percent Female	49.85%	49.40%
Percent Special Education	12.02%	11.74%
Percent Asian/Other	2.87%	2.98%
Percent Black	33.43%	31.13%
Percent Latinx	27.75%	30.26%
Percent White	35.95%	35.63%
Percent Students of Color	64.05%	64.37%
Percent English Learner	16.93%	21.82%
Mean Classroom Enrollment	39	34
3-Year Composite Evaluation Scores		
Mean 3-Yr TVAAS Index Composite (t-1)	0.81	
Less Effective (t-1)	25.54%	
Effective (t-1)	31.65%	
Highly Effective (t-1)	42.80%	
Bottom Quartile Composite (t-1)	22.02%	
25th-50th Quartile Composite (t-1)	30.57%	
50th-75th Quartile Composite (t-1)	28.69%	
Top Quartile Composite (t-1)	18.71%	
Observation Scores		
Mean Observation Score (t-1)		3.93
Bottom Quartile Observation (t-1)		22.07%
25th-5th Quartile Observation (t-1)		24.65%
50th-75th Quartile Observation (t-1)		28.92%
Top Quartile Observation (t-1)		24.35%
LOE Scores		
Less Effective (t-1) [LOE = 1-2]		10.63%
Effective (t-1) [LOE = 3]		22.94%
Highly Effective (t-1) [LOE = 4-5]		66.43%
N Observations	7,497	10,189

Note: Table shows descriptive characteristics of analytic covariates. Column 1 shows characteristics in the sample of teachers with available lagged TVAAS scores and column 2 shows characteristics in the sample of teachers with available lagged LOE scores. Descriptive statistics for student, teacher, and classroom characteristics are calculated at time *t*, while descriptive statistics for measures of teacher effectiveness are calculated at time *t-1*.

Table 1- 4 Mean Characteristics of Population

	Population Characteristics
Student Characteristics	
FRPL	81.55%
Special Education	12.35%
Female	45.50%
Immigrant	38.54%
Asian/Other	11.54%
Black	5.84%
Latinx	73.46%
White	9.16%
Retained	2.16%
Teacher Characteristics	
Logged Salary	$10.75
Female	90.42%
Age	41
Years of Experience	10
Asian/Other	0.48%
Black	23.51%
Latinx	0.48%
White	75.53%
Teacher of Color	24.47%
Masters or Higher	60.27%
Only Mainstream, No ESL Teacher	69.07%
No Mainstream, Only ESL Teacher	15.87%
Both Mainstream and ESL Teachers	15.06%
Classroom Peer Characteristics	
Percent FRPL	72.06%
Percent Female	49.68%
Percent Special Education	8.54%
Percent Asian/Other	4.02%
Percent Black	31.26%
Percent Latinx	24.88%
Percent White	39.84%
Percent Students of Color	60.16%
Percent English Learner	18.10%
Mean Classroom Enrollment	45

3-Year Composite Evaluation Scores	
Mean 3-year TVAAS Index Composite (t-1)	0.61
Less Effective (t-1)	29.21%
Effective (t-1)	29.94%
Highly Effective (t-1)	40.84%
Bottom Quartile Composite (t-1)	25.17%
25th-50th Quartile Composite (t-1)	30.49%
50th-75th Quartile Composite (t-1)	26.33%
Top Quartile Composite (t-1)	18.01%
Observation Scores	
Mean Observation Score (t-1)	3.90
Bottom Quartile Observation (t-1)	22.85%
25th-5th Quartile Observation (t-1)	25.39%
50th-75th Quartile Observation (t-1)	28.22%
Top Quartile Observation (t-1)	23.54%
TEAM Rubric	70.60%
LOE Scores	11.22%
Less Effective (t-1) [LOE = 1-2]	11.22%
Effective (t-1) [LOE = 3]	25.83%
Highly Effective (t-1) [LOE = 4-5]	62.95%

Note: Table shows descriptive characteristics of covariates used in the analysis. Descriptive statistics calculated for the full population of each category of covariate in 200 – 2014/15. Descriptive statistics for student, teacher, and classroom characteristics are calculated at time *t*, while descriptive statistics for measures of teacher effectiveness are calculated at time *t-1*. Descriptive statistics on EL student characteristics calculated for the population of EL in grades 3-8 who were ever ELs who were matched to a reading teacher. Descriptive statistics on teacher characteristics include all reading teachers who taught ELs in grades 3-8. Descriptive statistics on classroom characteristics include the peer characteristics of all reading classrooms (i.e. teacher-year-grade groupings) with ELs. Teacher evaluation scores include all prior year (lagged) scores for teachers with ELs.

Table 1- 5 Comparison of Baseline Hazard Specifications

Behavior of Logit Hazard	Model	BIC
Constant (time invariant)	$logit\ h(t_j) = \alpha_0$	8962.422
Linear	$logit\ h(t_j) = \alpha_j$	8948.574
Quadratic	$logit\ h(t_j) = \alpha_j + \alpha_j^2$	8888.695
Cubic	$logit\ h(t_j) = \alpha_j + \alpha_j^2 + \alpha_j^3$	8896.877
Quartic	$logit\ h(t_j) = \alpha_j + \alpha_j^2 + \alpha_j^3 + \alpha_j^4$	8869.634
Unrestricted (time dummies)	$logit\ h(t_j) = \alpha_1 D_1 + \cdots + \alpha_j D_J$	8829.652

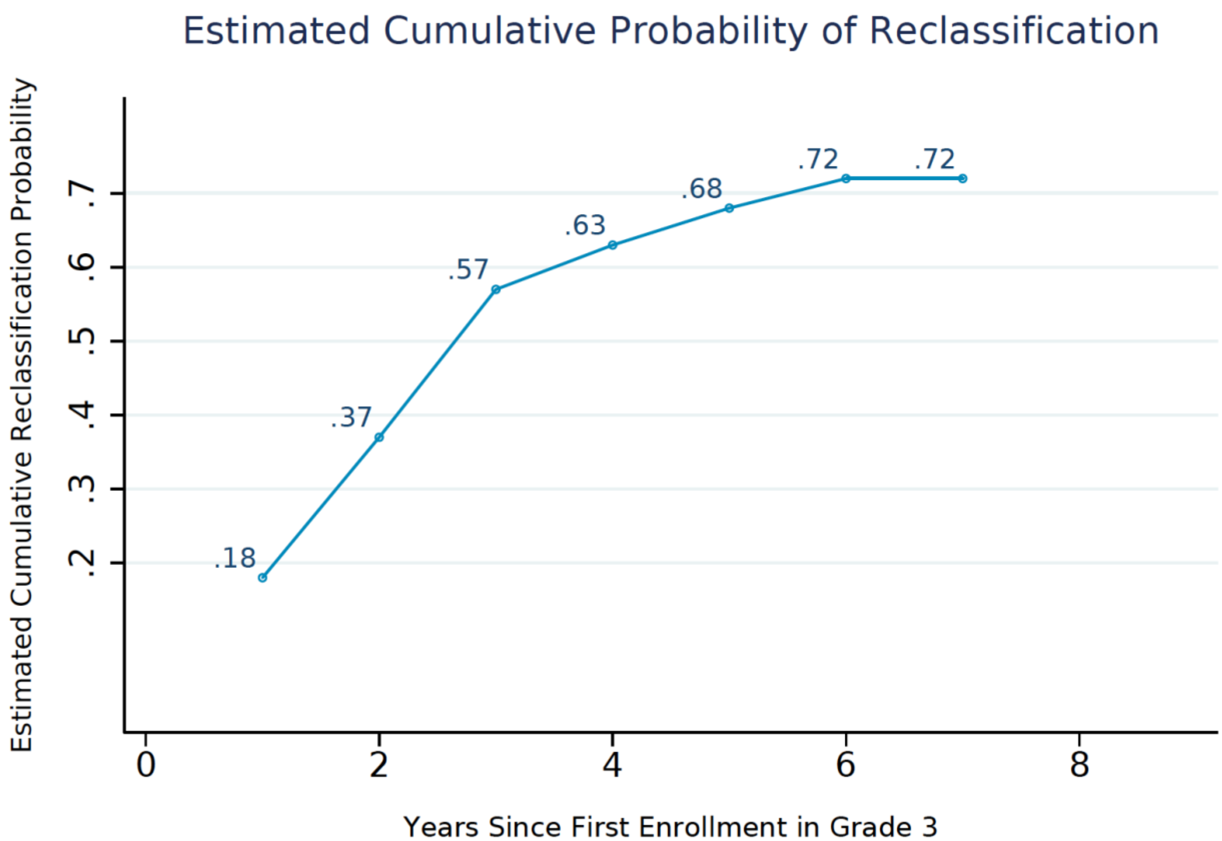
Note: j represents time periods. α_0 represents a constant logit hazard, which is a weighted average of all the values of time, given that time is omitted from this specification entirely. α_j represents a continuous modeling of time. $D_1 - D_j$ represent dummy variables for each time period 1 through j.

Table 1- 6 Life Table for Reclassification of ELs in Grades 3-8 who Enter Tennessee Public Schools in Kindergarten and Remain ELs in Tennessee Until Grade 3, Using Data from 2009/10 - 2014/15

Time	End of Grade (Approximate)	Beginning Total	Number Reclassified	Number Censored	Cumulative Hazard of Reclassification	Survival	Hazard
0	3	13,215	2,321	2,179	0.176	0.824	0.176
1	4	8,715	2,103	1,913	0.375	0.625	0.241
2	5	4,699	1,502	1,193	0.574	0.426	0.320
3	6	2,004	253	730	0.628	0.372	0.126
4	7	1,021	153	488	0.684	0.316	0.150
5	8	380	47	328	0.723	0.277	0.124
6	8	5	0	5	0.723	0.277	0.000

Note: Time represents the number of years following grade 3, where time 0 is grade 3, and time 5 is approximately grade 8. Time 6 represents students grade 8 for students who were retained for a grade level. In time 6 (i.e. 6 years after grade 3), students who were not reclassified were considered censored, as data on students in high school was not included in this analysis.

Figure 1- 2 Estimated Cumulative Probability of Reclassification for ELs in Grades 3-8 who Enter Tennessee Public Schools in Kindergarten and Remain ELs in Tennessee Until Grade 3, Using Data from 2009/10 - 2014/15



Note: Figure shows cumulative probability of reclassification for students who enrolled in Tennessee public school as ELs in kindergarten, and who were still enrolled as ELs in grade 3 onward. Time measured in number of years since grade 3, where 0 is grade 3. N= 13,215

Table 1- 7 Life Table of Reclassification of ELs in Grades K-12 who Enter Tennessee Public Schools in Kindergarten, Using Data from 2005/06 - 2014/15

Time	End of Grade (Approximate)	Beginning Total	Number Reclassified	Number Censored	Hazard All K-12	Hazard in Analytic Sample
0	K	68,517	6,001	9,790	0.088	
1	1	52,726	7,852	7,079	0.149	
2	2	37,795	6,847	5,137	0.181	
3	3	25,811	5,020	4,167	0.194	0.176
4	4	16,624	3,353	3,585	0.202	0.241
5	5	9,686	2,284	1,934	0.236	0.320
6	6	5,468	631	1,058	0.115	0.126
7	7	3,779	370	1,035	0.098	0.150
8	8	2,374	230	804	0.097	0.124
9	9	1,340	176	485	0.131	
10	10	679	46	358	0.068	
11	11	275	8	194	0.029	
12	12	73		73	0.000	

Note: Time represents the number of years following kindergarten, where time 0 is kindergarten, and time 12 is grade 12. In time 12, students who were not reclassified were considered censored, as data on students after high school was not included in this analysis. The last column contains the hazard of reclassification for ELs in the analytic sample in grades 3-8, as shown in Table 1-6 (N=13,215). Comparing the hazard rates of students in grades 3-8 in the population (Table 1-7) and sample (Table 1-6) shows that, even when removing ELs who exited the sample in grades K-2, the hazard rates of students in the sample in grades 3-8 are quite comparable to those of students in grades 3-8 in the full population.

Table 1- 8 Results from Discrete-Time Survival Analysis Models Estimating the Relationship Between Teacher Characteristics and ELs Hazard of Reclassification in Grades 3-8

	TVAAS Sample		LOE Sample	
	(1)	(2)	(1)	(2)
Teacher Characteristics				
Years of Experience	1.07**	1.04	1.06**	1.04
Teacher of Color	1.12*	1.16**	1.03	1.04
Master's Degree or Higher	1.09	1.10	1.04	1.04
N Observations	7,497	7,497	10,189	10,189
Student Controls	X	X	X	X
Classroom Controls		X		X
AIC	8606.54	8567.20	11462.75	11444.28
Log Likelihood	-4286.27	-4263.60	-5714.37	-5702.14
Degrees of Freedom	17.00	20.00	17.00	20.00

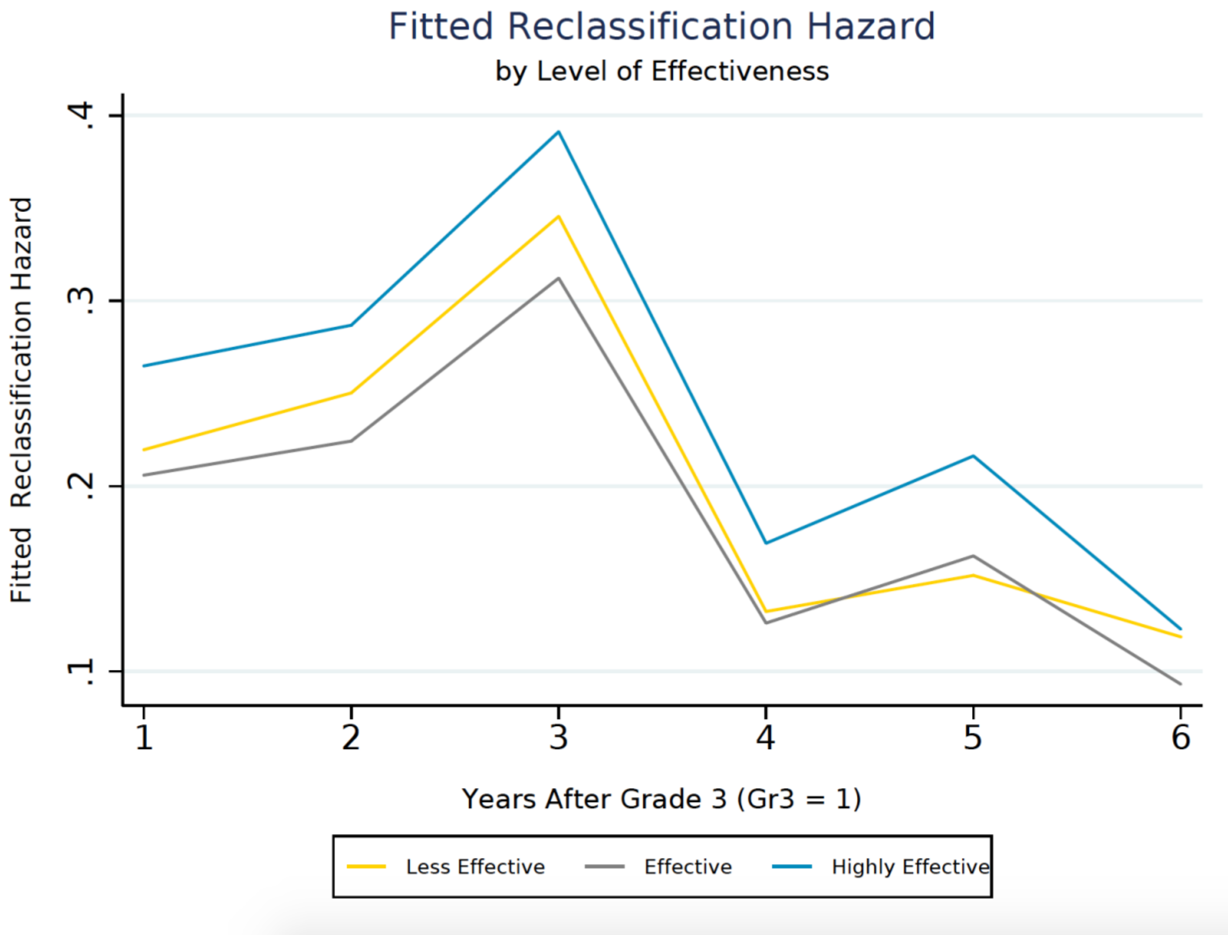
Note: Teacher characteristics are those of students' main classroom reading teacher as identified in the data (see manuscript for explanation of how main classroom reading teacher was identified). Models include controls for student demographics. Models in columns 2 add in controls for classroom characteristics. Exponentiated coefficients displayed as odds ratios. *p < 0.10 **p < 0.05 ***p<0.01.

Table 1- 9 Results from Discrete-Time Survival Analysis Models Estimating the Relationship Between Teacher Characteristics, Teacher Effectiveness, and ELs Hazard of Reclassification in Grades 3-8

	TVAAS Sample		LOE Sample		
	(1)	(2)	(3)	(4)	(5)
Teacher Characteristics					
Years of Experience	1.05*	1.05	1.02	1.03	1.03
Teacher of Color	1.14**	1.13**	1.05	1.04	0.98
Master's Degree or Higher	1.09	1.09	1.02	1.01	1.03
Measures of Teacher Effectiveness					
3-Year TVAAS Composite	1.05***				
Effective (TVAAS=3)		1.17**			
Highly Effective (TVAAS=4-5)		1.53***			
Average Observation Score			1.31***		
Observation Quartile=2				1.12*	
Observation Quartile=3				1.32***	
Observation Quartile=4				1.47***	
Effective (LOE=3)					0.93
Highly Effective (LOE=4-5)					1.27***
N Observations	7,497	7,497	10,189	10,189	10,189
Student Controls	X	X	X	X	X
Classroom Controls					
AIC	8578.06	8568.16	11427.45	11435.64	11406.17
Log Likelihood	-4271.03	-4265.08	-5694.73	-5696.82	-5682.08
Degrees of Freedom	18.00	20.00	19.00	22.00	22.00

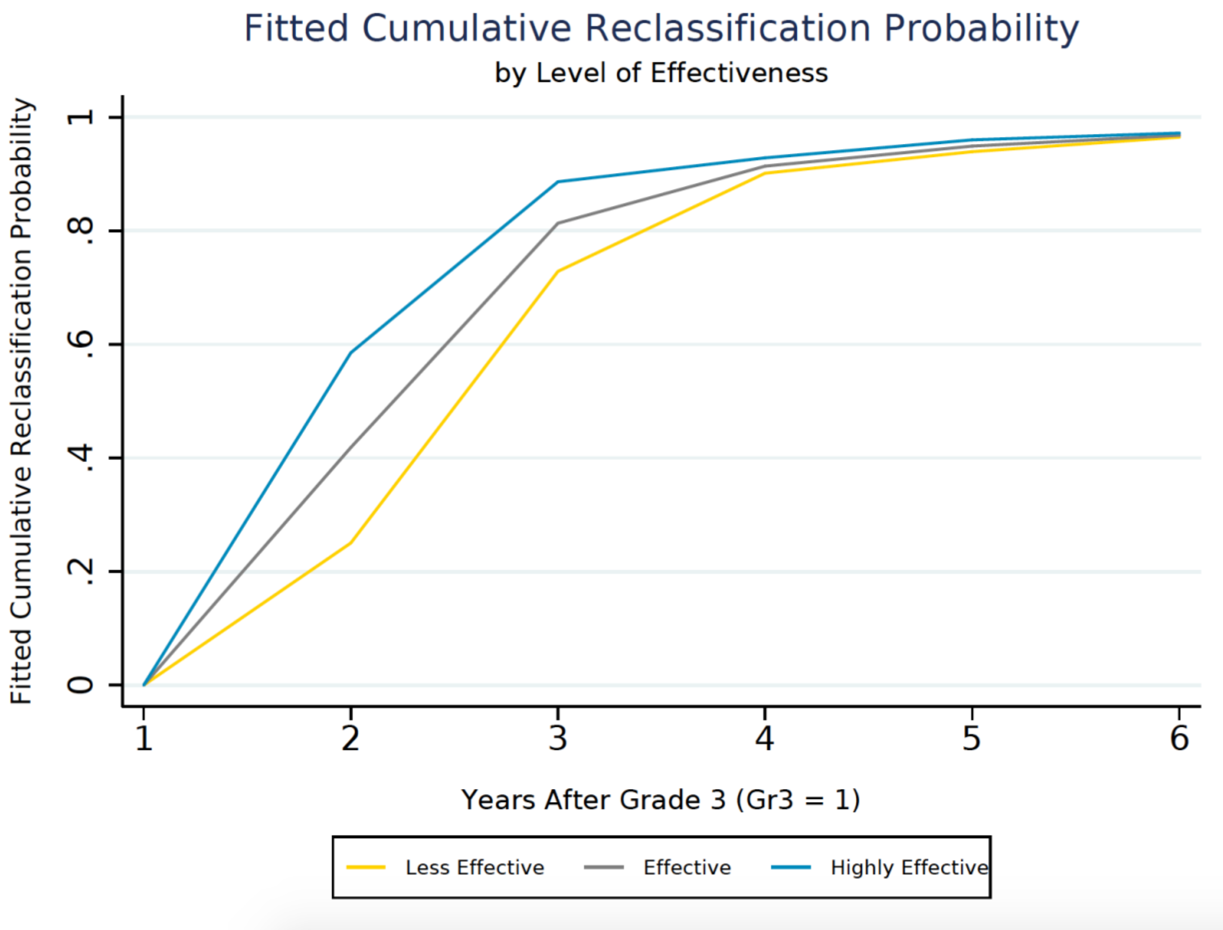
Note: Teacher characteristics are those of students' main classroom reading teacher as identified in the data (see manuscript for explanation of how main classroom reading teacher was identified). Measures of teacher effectiveness are lagged by one year (*t-1*). Models include controls for student demographics, but do not include classroom controls. Exponentiated coefficients displayed as odds ratios. *p < 0.10 **p < 0.05 ***p<0.01.

Figure 1- 3 Fitted Hazard of Reclassification, by Teachers' Overall Level of Effectiveness



Note: Figure displays fitted reclassification hazards of ELs in each year following grade 3 (where time 1 is grade 3) for models predicting EL' reclassification hazard using teachers' prior year LOE scores.

Figure 1- 4 Fitted Cumulative Probability of Reclassification, by Teachers' Overall Level of Effectiveness



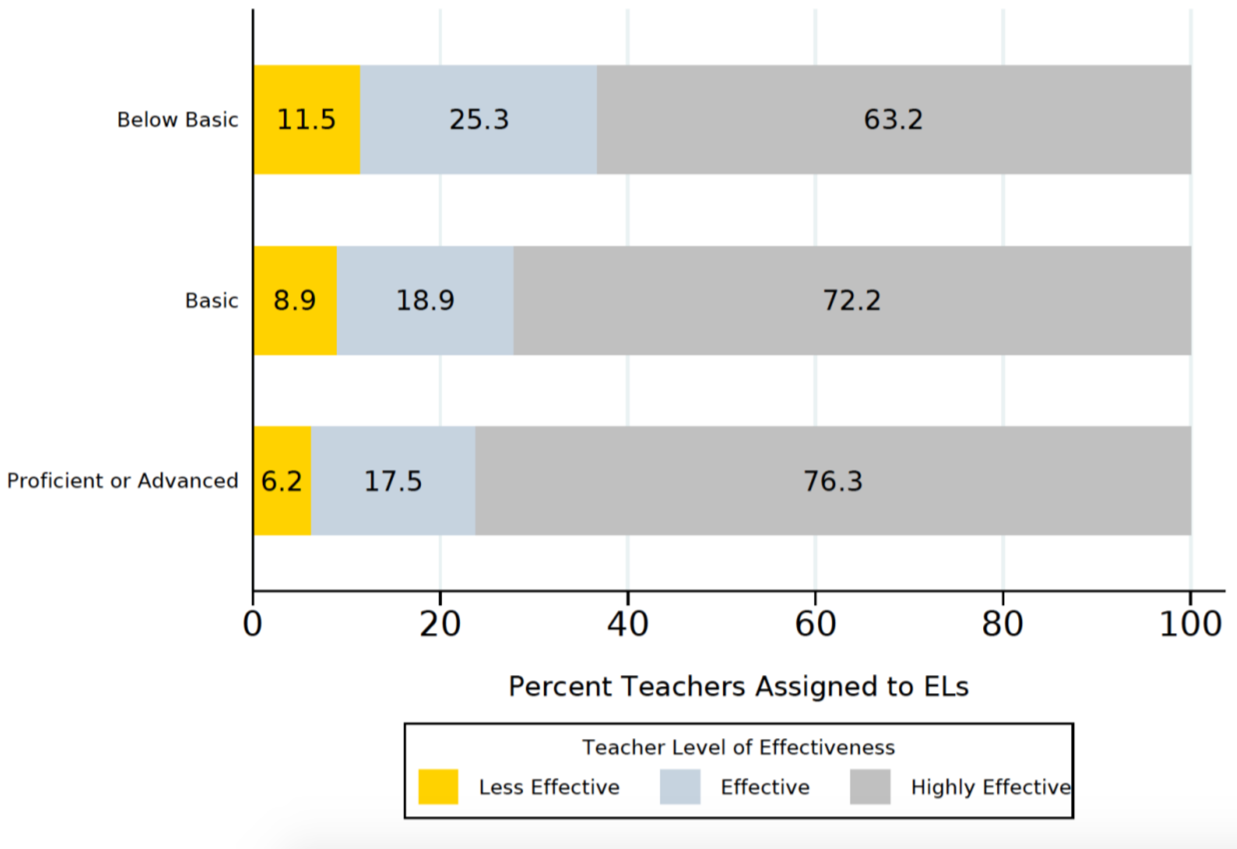
Note: Figure displays fitted cumulative probabilities of reclassification for ELs in each year following grade 3 (where time 1 is grade 3) for models predicting EL' reclassification hazard using teachers' prior year LOE scores.

Table 1- 10 Results from Discrete-Time Survival Analysis Models Estimating the Relationship Between Teacher Characteristics, Teacher Effectiveness, and ELs Hazard of Reclassification in Grades 3-8, Adding Classroom Covariates

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
Teacher Characteristics										
Years of Experience	1.05*	1.03	1.05	1.03	1.02	1.01	1.03	1.02	1.03	1.02
Teacher of Color	1.14**	1.17***	1.13**	1.17***	1.05	1.05	1.04	1.04	0.98	0.98
Master's Degree or Higher	1.09	1.09	1.09	1.09	1.02	1.02	1.01	1.02	1.03	1.03
Measures of Teacher Effectiveness										
3-Year TVAAS Composite	1.05***	1.04***								
Effective (TVAAS=3)			1.17**	1.18**						
Highly Effective (TVAAS=4-5)			1.53***	1.46***						
Average Observation Score					1.31***	1.28***				
Observation Quartile=2							1.12*	1.11		
Observation Quartile=3							1.32***	1.28***		
Observation Quartile=4							1.47***	1.42***		
Effective (LOE=3)									0.93	0.92
Highly Effective (LOE=4-5)									1.27***	1.25***
N Observations	7,497	7,497	7,497	7,497	10,189	10,189	10,189	10,189	10,189	10,189
Student Controls	X	X	X	X	X	X	X	X	X	X
Classroom Controls		X		X		X		X		X
AIC	8578.06	8546.26	8568.16	8538.65	11427.45	11416.23	11435.64	11424.55	11406.17	11402.30
Log Likelihood	-4271.03	-4252.13	-4265.08	-4247.32	-5694.73	-5686.12	-5696.82	-5688.27	-5682.08	-5677.15
Degrees of Freedom	18.00	21.00	20.00	23.00	19.00	22.00	22.00	25.00	22.00	25.00

Note: Teacher characteristics are those of students' main classroom reading teacher as identified in the data (see manuscript for explanation of how main classroom reading teacher was identified). Measures of teacher effectiveness are lagged by one year (t-1). Models in column "a" include controls for student demographics. Models in column "b" add controls for classroom characteristics. Exponentiated coefficients displayed as odds ratios. *p < 0.10 **p < 0.05 ***p<0.01.

Figure 1- 5 Percent of Teachers Assigned to ELs, Based on Teacher Effectiveness and ELs Reading Proficiency



Note: Figure shows the percent of less effective, effective, and highly effective teachers that ELs are assigned to across different reading proficiency levels. ELs' performance is based on their prior year reading score on the TCAP, the Tennessee state end of year summative exam. Teacher effectiveness measured using teachers' overall level of effectiveness (LOE) score.

Table 1- 11 Results from Logistic Regressions Predicting Assignment to Highly Effective Teacher, by EL Reading Proficiency

	Highly Effective - TVAAS Level	Highly Effective - Observation	Highly Effective - LOE
Basic Proficiency (t-1)	1.16***	0.88**	1.76***
Proficient/Advanced Proficient (t-1)	1.61***	1.14	2.44***
Observations	5,439	5,441	5,441
Student Controls	X	X	X
AIC	7496.43	6379.53	6800.55
Log Likelihood	-3738.21	-3179.76	-3390.28
Degrees of Freedom	10.00	10.00	10.00

Note: A highly effective teacher was defined as (1) a teacher scoring a 4 or 5 based on their prior year 3-year composite TVAAS level of effectiveness, (2) a teacher who scored in the topmost quartile based on their prior year average observation score, or (3) a teacher scoring a 4 or 5 based on their prior year overall level of effectiveness (LOE). EL reading proficiency measured using students' prior year score on the reading TCAP, Tennessee's end of year summative exam required for all students. Performance levels created by the Tennessee Department of Education based on state-wide proficiency scores determined by the state. The reference category is students scoring "below basic" on their prior year reading TCAP, which is the lowest level of achievement. Models include controls for student demographics. Sample is restricted to students with data on their prior year TCAP score, classroom characteristics, and all measures of teacher effectiveness. *p < 0.10 **p < 0.05 ***p<0.01.

Table 1- 12 Results from Discrete-Time Survival Analysis Models Estimating the Relationship Between Teacher Characteristics, Teacher Effectiveness, and ELs Hazard of Reclassification in Grades 3-8, Adding TCAP Scores

	TVAAS Sample				LOE Sample					
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
Teacher Characteristics										
Years of Experience	1.09**	1.06	1.08**	1.05	1.06	1.04	1.06	1.04	1.02	1.02
Teacher of Color	1.06	1.09	1.05	1.08	1.09	1.06	1.08	1.05	0.97	0.94
Master's Degree or Higher	1.17**	1.19***	1.18**	1.20***	1.16**	1.20***	1.15**	1.19***	1.16**	1.20***
Measures of Teacher Effectiveness										
3-Year TVAAS Composite	1.03***	1.02**								
Effective (TVAAS=3)			1.06	1.05						
Highly Effective (TVAAS=4-5)			1.32***	1.23**						
Average Observation Score					1.17***	1.13**				
Observation Quartile=2							1.01	1.03		
Observation Quartile=3							1.15	1.10		
Observation Quartile=4							1.28**	1.22**		
Effective (LOE=3)									0.81	0.78*
Highly Effective (LOE=4-5)									1.16	1.10
N Observations	5,439	5,439	5,439	5,439	5,441	5,441	5,441	5,441	5,441	5,441
Student Controls	X	X	X	X	X	X	X	X	X	X
Classroom Controls		X		X		X		X		X
Student Reading Performance	X	X	X	X	X	X	X	X	X	X
AIC	6165.80	6111.91	6162.84	6110.97	6188.84	6132.22	6190.39	6135.37	6126.37	6088.27
Log Likelihood	-3063.90	-3033.95	-3061.42	-3032.48	-3074.42	-3043.11	-3073.19	-3042.69	-3041.18	-3019.13
Degrees of Freedom	20.00	23.00	22.00	25.00	21.00	24.00	24.00	27.00	24.00	27.00

Note: Samples restricted to students who have prior year reading TCAP scores available. Teacher characteristics are those of students' main classroom reading teacher as identified in the data (see manuscript for explanation of how main classroom reading teacher was identified). Measures of teacher effectiveness are lagged by one year (t-1). Models in column "a" include controls for student demographics. Models in column "b" add controls for classroom characteristics. Exponentiated coefficients displayed as odds ratios. *p < 0.10 **p < 0.05 ***p<0.01.

Table 1- 13 Results from Discrete-Time Survival Analysis Models Estimating the Relationship Between Teacher Characteristics, Teacher Effectiveness, and ELs Hazard of Reclassification in Grades 3-8, Same Sample

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
Teacher Characteristics										
Years of Experience	1.02	1.00	1.02	1.00	0.99	0.97	1.00	0.98	0.97	0.96
Teacher of Color	1.16**	1.18***	1.15**	1.17**	1.16**	1.16**	1.16**	1.16**	1.05	1.04
Master's Degree or Higher	1.06	1.08	1.06	1.08	1.04	1.05	1.04	1.05	1.05	1.06
Measures of Teacher Effectiveness										
3-Year TVAAS Composite	1.05***	1.04***								
Effective (TVAAS=3)			1.23***	1.23***						
Highly Effective (TVAAS=4-5)			1.60***	1.52***						
Average Observation Score					1.36***	1.35***				
Observation Quartile=2							1.30***	1.32***		
Observation Quartile=3							1.37***	1.35***		
Observation Quartile=4							1.61***	1.59***		
Effective (LOE=3)									0.86	0.81*
Highly Effective (LOE=4-5)									1.34***	1.26**
N Observations	6,731	6,731	6,731	6,731	6,731	6,731	6,731	6,731	6,731	6,731
Student Controls	X	X	X	X	X	X	X	X	X	X
Classroom Controls		X		X		X		X		X
AIC	7761.66	7739.81	7747.12	7728.68	7756.61	7729.87	7765.60	7738.40	7678.96	7663.59
Log Likelihood	-3862.83	-3848.90	-3854.56	-3842.34	-3859.31	-3842.93	-3861.80	-3845.20	-3818.48	-3807.80
Degrees of Freedom	18.00	21.00	20.00	23.00	19.00	22.00	22.00	25.00	22.00	25.00

Note: Samples restricted to teachers with available data on all measures of teacher effectiveness. Teacher characteristics are those of students' main classroom reading teacher as identified in the data (see manuscript for explanation of how main classroom reading teacher was identified). Measures of teacher effectiveness are lagged by one year (t-1). Models in column "a" include controls for student demographics. Models in column "b" add controls for classroom characteristics. Exponentiated coefficients displayed as odds ratios. *p < 0.10 **p < 0.05 ***p<0.01.

Table 1- 14 Results from Discrete-Time Survival Analysis Models Estimating the Relationship Between Teacher Characteristics, Teacher Effectiveness, and ELs Hazard of Reclassification in Grades 3-8, Same Sample and Adding TCAP Scores

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
Teacher Characteristics										
Years of Experience	1.05	1.03	1.05	1.03	1.04	1.02	1.04	1.02	1.01	1.00
Teacher of Color	1.08	1.10	1.07	1.09	1.19**	1.17*	1.19**	1.17*	1.05	1.03
Master's Degree or Higher	1.18**	1.22***	1.18**	1.22***	1.16**	1.20**	1.16**	1.20**	1.18**	1.22***
Measures of Teacher Effectiveness										
3-Year TVAAS Composite	1.03***	1.02**								
Effective (TVAAS=3)			1.14	1.12						
Highly Effective (TVAAS=4-5)			1.41***	1.29***						
Average Observation Score					1.20***	1.19***				
Observation Quartile=2							1.05	1.09		
Observation Quartile=3							1.14	1.13		
Observation Quartile=4							1.32***	1.31**		
Effective (LOE=3)									0.78*	0.72**
Highly Effective (LOE=4-5)									1.14	1.05
N Observations	4,845	4,845	4,845	4,845	4,845	4,845	4,845	4,845	4,845	4,845
Student Controls	X	X	X	X	X	X	X	X	X	X
Classroom Controls		X		X		X		X		X
AIC	5539.61	5492.83	5533.15	5490.07	5537.80	5490.45	5541.01	5494.01	5494.53	5458.19
Log Likelihood	-2750.80	-2724.42	-2746.57	-2722.04	-2748.90	-2722.23	-2748.50	-2722.00	-2725.26	-2704.10
Degrees of Freedom	20.00	23.00	22.00	25.00	21.00	24.00	24.00	27.00	24.00	27.00

Note: Samples restricted to teachers with available data on all measures of teacher effectiveness and students with available prior year reading TCAP scores. Teacher characteristics are those of students' main classroom reading teacher as identified in the data (see manuscript for explanation of how main classroom reading teacher was identified). Measures of teacher effectiveness are lagged by one year (t-1). Models in column "a" include controls for student demographics. Models in column "b" add controls for classroom characteristics. Exponentiated coefficients displayed as odds ratios. *p < 0.10 **p < 0.05 ***p<0.01.

Table 1- 15 Results from Discrete-Time Survival Analysis Models with District Fixed Effects

	TVAAS Sample		LOE Sample		
	(1)	(2)	(3)	(4)	(5)
Teacher Characteristics					
Years of Experience	0.98	0.98	0.99	0.99	0.99
Teacher of Color	1.02	1.01	0.93	0.93	0.91
Master's Degree or Higher	1.08	1.08	1.03	1.03	1.03
Measures of Teacher Effectiveness					
3-Year TVAAS Composite	1.04***				
Effective (TVAAS=3)		1.12			
Highly Effective (TVAAS=4-5)		1.38***			
Average Observation Score			1.17***		
Observation Quartile=2				1.03	
Observation Quartile=3				1.16**	
Observation Quartile=4				1.25***	
Effective (LOE=3)					0.92
Highly Effective (LOE=4-5)					1.22**
N Observations	7,414	7,414	10,091	10,091	10,091
Student Controls	X	X	X	X	X
Classroom Controls	X	X	X	X	X
AIC	8302.51	8300.80	11201.10	11204.92	11184.86
Log Likelihood	-4058.25	-4056.40	-5503.55	-5503.46	-5493.43
Degrees of Freedom	123.00	125.00	127.00	130.00	130.00

Note: Samples are main analytic samples, excluding TCAP score. Models add in district fixed effects, represented by indicator variables for each school district. Teacher characteristics are those of students' main classroom reading teacher as identified in the data (see manuscript for explanation of how main classroom reading teacher was identified). Measures of teacher effectiveness are lagged by one year (t-1). Models include student and classroom controls. Exponentiated coefficients displayed as odds ratios. *p < 0.10 **p < 0.05 ***p<0.01.

Table 1- 16 Results from Discrete-Time Survival Analysis Models with District Urbanicity Fixed Effects

	TVAAS Sample		LOE Sample		
	(1)	(2)	(3)	(4)	(5)
Teacher Characteristics					
Years of Experience	1.03	1.02	1.01	1.01	1.02
Teacher of Color	1.21***	1.21***	1.06	1.05	0.99
Master's Degree or Higher	1.10	1.10*	1.02	1.02	1.03
Measures of Teacher Effectiveness					
3-Year TVAAS Composite	1.04***				
Effective (TVAAS=3)		1.18**			
Highly Effective (TVAAS=4-5)		1.47***			
Average Observation Score			1.28***		
Observation Quartile=2				1.11	
Observation Quartile=3				1.28***	
Observation Quartile=4				1.41***	
Effective (LOE=3)					0.92
Highly Effective (LOE=4-5)					1.24***
N Observations	7,497	7,497	10,189	10,189	10,189
Student Controls	X	X	X	X	X
Classroom Controls	X	X	X	X	X
AIC	8548.21	8540.25	11419.24	11427.50	11404.02
Log Likelihood	-4251.11	-4246.13	-5685.62	-5687.75	-5676.01
Degrees of Freedom	23.00	25.00	24.00	27.00	27.00

Note: Samples are main analytic samples, excluding TCAP score. Models add in fixed effects for district urbanicity. Data on district urbanicity were obtained from the National Center on Education Statistics (NCES). District urbanicity was classified as city, suburb, or town/rural community. Teacher characteristics are those of students' main classroom reading teacher as identified in the data (see manuscript for explanation of how main classroom reading teacher was identified). Measures of teacher effectiveness are lagged by one year (t-1). Models include student and classroom controls. Exponentiated coefficients displayed as odds ratios. *p < 0.10 **p < 0.05 ***p<0.01.

Table 1- 17 Results from Discrete-Time Survival Analysis Models with Tennessee CORE Region Fixed Effects

	TVAAS Sample		LOE Sample		
	(1)	(2)	(3)	(4)	(5)
Teacher Characteristics					
Years of Experience	1.02	1.02	1.01	1.01	1.02
Teacher of Color	0.98	0.98	0.94	0.93	0.92
Master's Degree or Higher	1.10*	1.10*	1.03	1.03	1.04
Measures of Teacher Effectiveness					
3-Year TVAAS Composite	1.04***				
Effective (TVAAS=3)		1.16*			
Highly Effective (TVAAS=4-5)		1.44***			
Average Observation Score			1.23***		
Observation Quartile=2				1.09	
Observation Quartile=3				1.23***	
Observation Quartile=4				1.34***	
Effective (LOE=3)					0.91
Highly Effective (LOE=4-5)					1.21**
N Observations	7,497	7,497	10,189	10,189	10,189
Student Controls	X	X	X	X	X
Classroom Controls	X	X	X	X	X
AIC	8526.66	8519.11	11387.35	11394.29	11382.25
Log Likelihood	-4240.33	-4235.56	-5669.68	-5671.15	-5665.13
Degrees of Freedom	23.00	25.00	24.00	27.00	27.00

Note: Samples are main analytic samples, excluding TCAP score. Models add in Tennessee CORE Region fixed effects. Tennessee Centers of Regional Excellence (CORE) are geographic regions across the state. Each of the eight CORE regions are overseen by a CORE office to help provide differentiated support to schools in the region. In this analysis, the eight regions are collapsed into three, representing West, Middle, and East Tennessee. Teacher characteristics are those of students' main classroom reading teacher as identified in the data (see manuscript for explanation of how main classroom reading teacher was identified). Measures of teacher effectiveness are lagged by one year (t-1). Models include student and classroom controls. Exponentiated coefficients displayed as odds ratios.
*p < 0.10 **p < 0.05 ***p<0.01.

Table 1- 18 Results from Discrete-Time Survival Analysis Models with District Fixed Effects and TCAP Scores

	TVAAS Sample		LOE Sample		
	(1)	(2)	(3)	(4)	(5)
Teacher Characteristics					
Years of Experience	1.01	1.01	1.00	1.00	0.98
Teacher of Color	0.97	0.96	0.93	0.92	0.90
Master's Degree or Higher	1.19**	1.19**	1.20***	1.20**	1.21***
Measures of Teacher Effectiveness					
3-Year TVAAS Composite	1.03**				
Effective (TVAAS=3)		1.00			
Highly Effective (TVAAS=4-5)		1.18**			
Average Observation Score			1.03		
Observation Quartile=2				0.92	
Observation Quartile=3				0.98	
Observation Quartile=4				1.06	
Effective (LOE=3)					0.82
Highly Effective (LOE=4-5)					1.15
N Observations	5,362	5,362	5,355	5,355	5,355
Student Controls	X	X	X	X	X
Classroom Controls	X	X	X	X	X
Student Performance Reading	X	X	X	X	X
AIC	5983.42	5984.78	5964.64	5966.76	5947.31
Log Likelihood	-2904.71	-2904.39	-2894.32	-2893.38	-2883.66
Degrees of Freedom	119.00	121.00	122.00	125.00	125.00

Note: Samples include only students with available prior year TCAP scores and other analytic covariates. Models add in district fixed effects and controls for students' prior year reading TCAP scores. Teacher characteristics are those of students' main classroom reading teacher as identified in the data (see manuscript for explanation of how main classroom reading teacher was identified). Measures of teacher effectiveness are lagged by one year (t-1). Models include controls for student and classroom characteristics and students' prior year reading TCAP score. Exponentiated coefficients displayed as odds ratios.
*p < 0.10 **p < 0.05 ***p<0.01.

Table 1- 19 Results from Discrete-Time Survival Analysis Models with District Urbanicity Fixed Effects and TCAP Scores

	TVAAS Sample		LOE Sample		
	(1)	(2)	(3)	(4)	(5)
Teacher Characteristics					
Years of Experience	1.05	1.05	1.04	1.04	1.02
Teacher of Color	1.15*	1.14*	1.09	1.09	0.98
Master's Degree or Higher	1.20***	1.20***	1.21***	1.21***	1.22***
Measures of Teacher Effectiveness					
3-Year TVAAS Composite	1.02**				
Effective (TVAAS=3)		1.05			
Highly Effective (TVAAS=4-5)		1.23**			
Average Observation Score			1.13**		
Observation Quartile=2				1.02	
Observation Quartile=3				1.10	
Observation Quartile=4				1.21*	
Effective (LOE=3)					0.78*
Highly Effective (LOE=4-5)					1.10
N Observations	5,439	5,439	5,441	5,441	5,441
Student Controls	X	X	X	X	X
Classroom Controls	X	X	X	X	X
Student Performance Reading	X	X	X	X	X
AIC	6112.55	6111.70	6132.35	6135.50	6086.73
Log Likelihood	-3032.27	-3030.85	-3041.18	-3040.75	-3016.37
Degrees of Freedom	25.00	27.00	26.00	29.00	29.00

Note: Samples include only students with available prior year TCAP scores and other analytic covariates. Models add in urbanicity fixed effects and controls for students' prior year reading TCAP scores. Data on district urbanicity were obtained from the National Center on Education Statistics (NCES). District urbanicity was classified as city, suburb, or town/rural community. Teacher characteristics are those of students' main classroom reading teacher as identified in the data (see manuscript for explanation of how main classroom reading teacher was identified). Measures of teacher effectiveness are lagged by one year (t-1). Models include controls for student and classroom characteristics and students' prior year reading TCAP score. Exponentiated coefficients displayed as odds ratios.
*p < 0.10 **p < 0.05 ***p<0.01.

Table 1- 20 Results from Discrete-Time Survival Analysis Models with Tennessee CORE Region Fixed Effects and TCAP Scores

	TVAAS Sample		LOE Sample		
	(1)	(2)	(3)	(4)	(5)
Teacher Characteristics					
Years of Experience	1.05	1.05	1.04	1.03	1.02
Teacher of Color	0.95	0.94	0.92	0.91	0.89
Master's Degree or Higher	1.19***	1.20***	1.21***	1.21***	1.23***
Measures of Teacher Effectiveness					
3-Year TVAAS Composite	1.02**				
Effective (TVAAS=3)		1.04			
Highly Effective (TVAAS=4-5)		1.23**			
Average Observation Score			1.09		
Observation Quartile=2				1.00	
Observation Quartile=3				1.07	
Observation Quartile=4				1.16	
Effective (LOE=3)					0.77**
Highly Effective (LOE=4-5)					1.08
N Observations	5,439	5,439	5,441	5,441	5,441
Student Controls	X	X	X	X	X
Classroom Controls	X	X	X	X	X
Student Performance Reading	X	X	X	X	X
AIC	6105.97	6104.66	6112.49	6115.44	6076.90
Log Likelihood	-3028.98	-3027.33	-3031.24	-3030.72	-3011.45
Degrees of Freedom	25.00	27.00	26.00	29.00	29.00

Note: Samples include only students with available prior year TCAP scores and other analytic covariates. Models add in Tennessee CORE Region fixed effects and controls for student's prior year reading TCAP scores. Tennessee Centers of Regional Excellence (CORE) are geographic regions across the state. Each of the eight CORE regions are overseen by a CORE office to help provide differentiated support to schools in the region. In this analysis, the eight regions are collapsed into three, representing West, Middle, and East Tennessee. Teacher characteristics are those of students' main classroom reading teacher as identified in the data (see manuscript for explanation of how main classroom reading teacher was identified). Measures of teacher effectiveness are lagged by one year (t-1). Models include controls for student and classroom characteristics and students' prior year reading TCAP score. Exponentiated coefficients displayed as odds ratios.
*p < 0.10 **p < 0.05 ***p<0.01.

Table 1- 21 Results from Discrete-Time Survival Analysis Models Using Clog-log Link Function, No TCAP Scores

	TVAAS Sample				LOE Sample					
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
Teacher Characteristics										
Years of Experience	1.04*	1.03	1.04*	1.02	1.02	1.01	1.02	1.01	1.02	1.02
Teacher of Color	1.12**	1.15***	1.12**	1.14***	1.04	1.05	1.04	1.04	0.99	0.99
Master's Degree or Higher	1.08	1.08*	1.08*	1.08*	1.02	1.02	1.02	1.02	1.03	1.03
Measures of Teacher Effectiveness										
3-Year TVAAS Composite	1.04***	1.03***								
Effective (TVAAS=3)			1.15**	1.15**						
Highly Effective (TVAAS=4-5)			1.42***	1.37***						
Average Observation Score					1.25***	1.23***				
Observation Quartile=2							1.10	1.09		
Observation Quartile=3							1.27***	1.23***		
Observation Quartile=4							1.39***	1.34***		
Effective (LOE=3)									0.94	0.93
Highly Effective (LOE=4-5)									1.22***	1.20***
N Observations	7,497	7,497	7,497	7,497	10,189	10,189	10,189	10,189	10,189	10,189
Student Controls	X	X	X	X	X	X	X	X	X	X
Classroom Controls		X		X		X		X		X
AIC	8580.44	8549.10	8570.21	8540.65	11430.53	11419.61	11438.01	11427.54	11410.23	11406.14
Log Likelihood	-4272.22	-4253.55	-4266.11	-4248.32	-5696.27	-5687.80	-5698.01	-5689.77	-5684.11	-5679.07
Degrees of Freedom	18.00	21.00	20.00	23.00	19.00	22.00	22.00	25.00	22.00	25.00

Note: Table shows results from Table 1-10 estimated using the complementary log-log (clog-log) link function. Teacher characteristics are those of students' main classroom reading teacher as identified in the data (see manuscript for explanation of how main classroom reading teacher was identified). Measures of teacher effectiveness are lagged by one year (t-1). Exponentiated coefficients displayed as odds ratios. *p < 0.10 **p < 0.05 ***p<0.01.

Table 1- 22 Results from Discrete-Time Survival Analysis Models Using Clog-log Link Function, with TCAP Scores

	TVAAS Sample				LOE Sample					
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
Teacher Characteristics										
Teacher Years of Experience (Main)	1.06**	1.04	1.06**	1.04	1.04	1.03	1.04	1.03	1.01	1.01
Teacher of Color (Main)	1.06	1.09	1.06	1.08	1.08	1.05	1.08	1.05	0.98	0.95
Teacher Master's or Higher (Main)	1.15***	1.16***	1.15***	1.16***	1.13**	1.16***	1.12**	1.16***	1.13**	1.17***
Measures of Teacher Effectiveness										
3-Year TVAAS Composite	1.02***	1.02**								
Effective (TVAAS=3)			1.06	1.05						
Highly Effective (TVAAS=4-5)			1.25***	1.19**						
Average Observation Score					1.14***	1.11**				
Observation Quartile=2							1.00	1.01		
Observation Quartile=3							1.12	1.09		
Observation Quartile=4							1.23**	1.18**		
Effective (LOE=3)									0.83*	0.81**
Highly Effective (LOE=4-5)									1.12	1.08
N Observations	5,439	5,439	5,439	5,439	5,441	5,441	5,441	5,441	5,441	5,441
Student Controls	X	X	X	X	X	X	X	X	X	X
Classroom Controls		X		X		X		X		X
Student Performance Reading	X	X	X	X	X	X	X	X	X	X
AIC	6174.36	6119.67	6171.20	6118.15	6195.60	6137.84	6196.61	6140.50	6134.45	6093.49
Log Likelihood	-3068.18	-3037.84	-3065.60	-3036.07	-3077.80	-3045.92	-3076.31	-3045.25	-3045.22	-3021.74
Degrees of Freedom	20.00	23.00	22.00	25.00	21.00	24.00	24.00	27.00	24.00	27.00

Note: Table shows results from Table 1-12 estimated using the complementary log-log (clog-log) link function. Samples restricted to students who have prior year reading TCAP scores. Teacher characteristics are those of students' main classroom reading teacher as identified in the data (see manuscript for explanation of how main classroom reading teacher was identified). Measures of teacher effectiveness are lagged by one year (t-1). Exponentiated coefficients displayed as odds ratios. *p < 0.10 **p < 0.05 ***p<0.01.

Appendix

Table A1- 1 Roles of Teachers in Main Analytic Samples

	TVAAS Sample	LOE Sample	TVAAS (%)	LOE (%)
Art Teacher (Elementary)	5	5	0.1%	0.0%
Assistant Principal (Elementary)	2		0.0%	0.0%
Chapter 1 Teacher Elementary	42	57	0.6%	0.6%
Chapter 1 Teacher Secondary	5	28	0.1%	0.3%
Grade 1 Teacher	245	337	3.3%	3.3%
Grade 2 Teacher	431	634	5.7%	6.2%
Grade 3 Teacher	1421	3577	19.0%	35.1%
Grade 4 Teacher	2282	2447	30.4%	24.0%
Grade 5 Teacher	1542	1476	20.6%	14.5%
Grade 6 Teacher	588	466	7.8%	4.6%
Grade 7 Teacher	307	263	4.1%	2.6%
Grade 8 Teacher	239	212	3.2%	2.1%
Grade 9-12 Teacher	16	9	0.2%	0.1%
Kindergarten	164	271	2.2%	2.7%
Librarian (Elementary/Secondary)		1	0.0%	0.0%
Other System Wide w/wo CL	7	10	0.1%	0.1%
Pre-K Teacher	30	51	0.4%	0.5%
Reading Specialist	8	15	0.1%	0.1%
School Counselor (Elementary)		2	0.0%	0.0%
Special Education Options 7,8,9	1	9	0.0%	0.1%
Special Education Related Services	2	2	0.0%	0.0%
Special Education Teacher (Elementary)	35	81	0.5%	0.8%
Special Education Teacher (Secondary)	12	25	0.2%	0.2%
Substitute Teacher		1	0.0%	0.0%
Unknown	113	210	1.5%	2.1%
Total	7,497	10,189	100%	100%

Note: The first two columns present the raw counts of teachers in each sample who hold a given position as identified in the staff role data. The latter two columns present the percentage of the sample represented by teachers in this role.

Chapter 3

On Time but Still Behind: Variation in Parental Education and First-Generation Students' First-Term Academic Achievement

It is well-documented that first-generation students face numerous obstacles in accessing postsecondary education. First-generation students are often less resourced than their non-first-generation peers in terms of access to information around college-going, financial and educational resources, and educational opportunities (Adelman, 1993; Atherton, 2014; Engle, 2007; Orbe, 2004; Stephens et al., 2012; Wildhagen, 2015). First-generation students are also more likely to take remedial coursework, be less academically prepared to succeed in a traditional college environment, come from more under-resourced, low-income backgrounds, or have more personal responsibilities (e.g. family obligations, employment) than their non-first-generation peers (Atherton, 2014; Bui, 2002; Byrd & Macdonald, 2005; Furquim et al., 2017; McCarron & Inkelas, 2006; Terenzini et al., 1996). Several quantitative and qualitative studies link the obstacles first-generation students face to lower college GPAs, lower rates of persistence, and greater drop-out rates (D'Amico & Dika, 2013; Martinez et al., 2009; Terenzini et al., 1996).

At the core, these gaps in access and opportunities arise from differences in first-generation students' cultural, social, and human capital due to differences in their parents level of education (Astin, 1975; Bean, 1983; Bills, 2003; Bourdieu, 1986; Coleman, 1988; Johnson, 2008; Martin Lohfink & Paulsen, 2005; Martinez et al., 2009; Pascarella et al., 2004; Peralta & Klonowski, 2017; Schwartz et al., 2017; Tinto, 1993; Tobolowsky et al., 2017; Toutkoushian et al., 2019; Wilbur & Roscigno, 2016). Degree-holding parents possess greater cultural and social capital around college-going and have more financial capital to support their children's pre-college development and transition to college. Drawing from their own college experiences, degree-holding parents are better able to pass down information on how the college admissions and enrollment process works and how to navigate the “hidden curricula” of education, such as succeeding in college coursework, obtaining internships, and fulfilling graduation requirements (Anyon, 1980; Golann, 2015; Willis, 1981).

Recent work emphasizes the importance of understanding the relationship between alternate definitions of first-generation status and students’ postsecondary outcomes (Toutkoushian et al., 2018, 2019). To the extent that policies and programs include different groups of students in their definition of first-generation (D’Amico & Dika, 2013; Ishitani, 2003, 2006, 2016; Terenzini et al., 1996; Ward et al., 2012; Whitley et al., 2018), it is of policy relevance to understand how postsecondary outcomes differ for alternative definitions of first-generation students. Numerous studies compare definitions of first-generation capturing different “amounts” of parental capital using the number of degree-holding parents. In assessing long-term outcomes such as graduation rates and persistence, these studies find that first-generation students who have one degree-holding parent perform better than students who have no degree-holding parents, but worse than students who have two degree-holding parents (Cragg, 2009; D’Allegro & Kerns, 2010; Fike & Fike, 2008; Ishitani, 2006, 2016; Nunez & Cuccaro-Alamin, 1998; Redford et al., 2017; Toutkoushian et al., 2019; Warburton et al., 2001). Most recently, a study by Toutkoushian and colleagues (2019) uses nationally representative data from the Education Longitudinal Study of 2002 to describe differences in graduation rates for first-generation students defined in twelve different ways.

Though many of these studies use nationally representative survey data, most focus primarily on data at only two- or only four-year institutions, and only a few are able to control for the types of institutions that students attend (Cragg, 2009; Ishitani, 2016; Toutkoushian et al., 2019). Studies also focus on students' long-term degree-attainment outcomes and few examine proximal outcomes beyond enrollment. There remains a need to document differences in students' access to different levels of parental capital as it relates to more granular, credit attainment outcomes. Assessing term-level differences can paint a clear picture as to how quickly gaps in first-generation students' postsecondary attainment can develop. To the extent that first-generation students have fewer financial and academic resources, it is also important to discern whether there is heterogeneity in the estimates across not only college-going capital, as measured by parental education level, but also financial resources and academic preparedness.

The present study is a comprehensive look at the recent landscape of the first-generation college students enrolled in public institutions of higher education in Tennessee. Drawing from a longitudinal, administrative dataset containing information on students' institutions and major of enrollment, credit attainment, admissions test scores, demographics, financial aid eligibility, and family financial resources, this study uses institution fixed effects and a rich set of controls to document differences in first-generation and non-first-generation students' first-term credit outcomes. Subgroup analyses estimate differences in first-generation students based on level of parental education as well as differences between students for whom only their mother or only their father hold a college degree. Finally, given that first-generation students often have less access to human capital resources necessary for college success, this analysis examines potential heterogeneity based on students' access to financial resources and their level of academic preparation. This study examines the following questions:

1. What is the relationship between students' first-generation status and their first-term credit attainment and GPA?

2. How does this relationship vary based on levels of parental education?
3. To what extent does the relationship between students' first-generation status and students' first-term attainment vary by students' access to financial resources and level of academic preparedness?

Findings show that first-generation students attempt and earn fewer credits than their non-first-generation peers in their first-term of college. Stratifying the definition of first-generation students reveals that first-generation students with one degree-holding parent perform slightly better than first-generation students with no degree-holding parents. Further stratification of first-generation students reveals some differences amongst first-generation students for whom only their father has a college degree and first-generation students for whom only their mother has a degree or neither parent has a college degree, though this finding may be a result of gender-differences in income and education.

Heterogeneity analyses note few differences in the marginal associations for first-generation and non-first-generation with differential financial resources or academic preparedness. Significant interactions on cumulative credit and GPA variables supports the idea that students with greater resources are better able to access to educational opportunities for postsecondary credit attainment prior to their first term. Results substantiate prior findings, namely, that the "amount" of parental capital around college-going that students have access to matters, both when examining outcomes such as degree attainment, as in prior work, (Cragg, 2009; Fike & Fike, 2008; Ishitani, 2003, 2006, 2016; Redford et al., 2017; Toutkoushian et al., 2019; Warburton et al., 2001), and when examining granular, term-specific outcomes, as examined in the present study.

This study documents differences for first-generation students using granular, term-level outcomes and helps researchers and policymakers alike understand how key differences in students' resources may relate to differences in first-generation students' postsecondary outcomes. Finally, this study underscores the importance of providing first-generation students informational supports early—not only when applying to college, but also once enrolled.

Conceptual Framework

Scholars contend that differences in first-generation and non-first-generation students' pre-college and college outcomes stem from differences in first-generation students' cultural and social capital (Astin, 1975; Bean, 1983; Bills, 2003; Bourdieu, 1986; Coleman, 1988; Johnson, 2008; Martin Lohfink & Paulsen, 2005; Martinez et al., 2009; Pascarella et al., 2004; Schwartz et al., 2017; Tinto, 1993; Tobolowsky et al., 2017; Toutkoushian et al., 2019; Wilbur & Roscigno, 2016). Cultural capital (Berger, 2000; Bourdieu, 1977, 1986; Jæger & Karlson, 2018; Møllegaard & Jæger, 2015; Tan, 2017) is the "degree of ease and familiarity that one has with the 'dominant' culture of a society" (Bills, 2003, p. 90), while social capital can be thought of as the relationships between individuals that facilitate the transaction of other capital, like cultural, human, or even additional social capital (Bourdieu, 1977, 1986; Coleman, 1988; Field, 2016; Lin, 2002; Møllegaard & Jæger, 2015; Moschetti & Hudley, 2015). High levels of cultural and social capital are crucial to succeeding during the transition to postsecondary institutions and once enrolled. Institutional norms and expectations align with the rules and values of dominant classes; students with higher levels of cultural and social capital can better navigate these expectations, while those who have less access to cultural and social capital may struggle (Collier & Morgan, 2007; Stephens et al., 2012).

For instance, a study by Collier and Morgan (2007) examining qualitative focus group data of first-generation and non-first-generation students at a large public university finds considerable incongruities between first-generation students and faculty expectations around coursework. First-generation students expressed a greater need for clarity on professors' expectations, such as how in depth the professor expected students to complete reading assignments, how to navigate the syllabus, and the level of detail professors wanted in writing assignments. First-generation students also described not always understanding professors' speech, believing it to be full of jargon or inaccessible to students. In juxtaposition, professors often thought they were being clear in these expectations and speech. Non-first-generation students had similar expectations but reported markedly fewer problems compared to their first-generation peers. The authors note that, due to these fundamental incongruities in role expectations and behaviors, first-generation students experienced negative academic consequences such as not allotting sufficient time to master course skills or performing course tasks in the ways the professor expected.

Dumais (2002) notes that, while institutions expect students to recognize and use the values of dominant culture, they do not provide students ways to learn these rules. Instead, cultural capital about dominant class behaviors and norms are expected to be transmitted to students by families. First-generation students likely have less access to family expertise about navigating dominant class behaviors and norms and cannot rely on their parents to help them perform the role expectations outlined by postsecondary institutions. Parents with college degrees may have greater familiarity with the college expectations and may familiarize their children with these norms and expectations from an early age, giving their children an advantage (Martinez et al., 2009; Palbusa & Gauvain, 2017). In contrast, parents who do not have a college degree may be less familiar with college life and might not have the experience, knowledge, or connections to help their students navigate the process, leaving their children comparatively disadvantaged (Martinez et al., 2009; Palbusa & Gauvain, 2017). As Collier and Morgan (2007) argue, college success requires both an understanding of the course material and an understanding of faculty expectations. To do this well, students must have both cultural capital and social capital.

In addition to cultural and social capital, students' human capital, which students typically access through their parents, also plays a pivotal role in their college access and success (Toutkoushian et al., 2019; Wilbur & Roscigno, 2016). Compared to degree-holding parents, parents who do not hold a college degree may be less equipped to provide their children with information, financial resources, and academic preparation for college. Parents who hold college degrees may have better knowledge about the requirements of college compared to parents who have started a degree but did not complete it or parents who never attended postsecondary education (Gibbons et al., 2019; Padgett et al., 2012; Pascarella et al., 2004; Peralta & Klonowski, 2017). Consequently, degree-holding parents may be better positioned to pass this information to their children. Furthermore, college-educated parents on average have greater financial resources which can be used to alleviate the costs and potential financial risks, associated with college, decreasing students' opportunity cost and financial burden (Engle, 2007; Terenzini et al., 1996). Degree-holding parents may also be able to better support their children's academic preparation, using their financial resources or own knowledge and preparation to secure their children access to precollege education opportunities and resources (Choy, 2001; Terenzini et al., 1996; Warburton et al., 2001). In other words, parents of first-generation students may be less prepared to pass on their "parental capital" (whether it be human, cultural, or social) on to their children, ultimately making the transition to college more challenging.

Literature

Defining First-Generation College Students

The term "first-generation college student" was first used as a category to identify students eligible for federally funded outreach programs for traditionally disadvantaged students under the Higher Education Act in the early 1960s. Such programs included Upward Bound, Talent Search, and Student Support Services (Ward et al., 2012). The Higher Education Act defines first-generation students as (a) "An individual both of whose parents did not complete a baccalaureate degree"; or (b) "In the case of any individual who regularly resided with and received support from only one parent, an individual whose only such parent did not complete a baccalaureate degree" (Higher Education Act of 1965, 1998 Higher Education Act Amendments, Subpart 2—Federal Early Outreach and Student Services Programs, 1998, para. f1). While some university, policy, or research endeavors have ascribed to the federal definition, others have defined first-generation students in a variety of ways (D'Amico & Dika, 2013; Ishitani, 2016; Terenzini et al., 1996; Warburton et al., 2001; Whitley et al., 2018).

As parental capital is considered the primary driver in the gap between first-generation and non-first-generation students' access to and success during college, scholars emphasize the importance of measuring how variation in students' access to parental capital is related to students' postsecondary outcomes (Cragg, 2009; D'Allegro & Kerns, 2010; Toutkoushian et al., 2019; Warburton et al., 2001). Prior work examining varying definitions of first-generation student status compare different "amounts" of parental capital using the number of degree-holding parents (Cragg, 2009; D’Allegro & Kerns, 2010; Fike & Fike, 2008; Ishitani, 2003, 2006, 2016; Nunez & Cuccaro-Alamin, 1998; Redford et al., 2017; Toutkoushian et al., 2019; Warburton et al., 2001). A recent study by Toutkoushian and colleges (2019) uses nationally representative survey data to assess eight definitions of first-generation students enrolled in both two- and four-year college regarding students’ college completion. The study documents persistent gaps in college completion rates by all levels of parental education, defining using data on whether a parent had any college, an associate’s degree, some four-year coursework but no degree, or a bachelor’s degree. Prior work does not examine variation based on which parent has the degree, though related studies find that when fathers are more involved in their families or learning experiences, children have improved educational outcomes, such as higher grades, lower levels of discipline, and increased problem solving capacity, among other cognitive behaviors (Koestner et al., 1990; McBride et al., 2009; Nord et al., 1997; Pruett, 2001).

Factors Affecting College Enrollment

Prior work has examined several factors that affect first-generation students’ college access and success once enrolled, including (1) information about college, (2) college costs and access to financial resources, (3) academic preparedness, and (4) demographic characteristics (Atherton, 2014; Barry et al., 2009; D’Amico & Dika, 2013; Engle, 2007; Inman & Mayes, 1999; Johnson, 2008; Martinez et al., 2009; Page & Scott-Clayton, 2016; Pascarella et al., 2004; Perna, 2006; Schwartz et al., 2017; Terenzini et al., 1996; Tobolowsky et al., 2017; Toutkoushian et al., 2019; Wilbur & Roscigno, 2016). While each of these components play a role in college success for all students, these aspects are especially challenging for students from first-generation backgrounds.

Information About College

The first barrier is the challenge of processing and using information about college. Students may lack sufficient information about how the college admissions process works or may have too much information about the process and may not be able to strategically parse through the information. In either case, the inability of parsing out information prevents students from "engaging optimally" with the college admissions process (Page & Scott-Clayton, 2016, p. 10). Examples of important information students need for college includes information on how to complete the streams of paperwork required, the importance of campus tours and how to maximize the visit, knowing which courses to take during both high school and college to attain academic success, and which tests to take.

Once enrolled, students may continue to need additional supports to access and understand information about college completion. First-generation students in particular may face additional challenges, such as a lack of sufficient institutional, family, and peer supports during school (Adelman, 1993; Dennis et al., 2005; Ishitani, 2006; Orbe, 2004; Stephens et al., 2012). A longitudinal study of first-generation students of color found that students' personal- and career-related motivation to attend college was positively related to their adjustment in college, while a lack of peer support was negatively related to students' adjustment in college as well as students' GPA (Dennis et al., 2005). Another recent report investigated the role of parent-student communication in first-year students' transition to postsecondary education. Using survey data on first-year students at a large public university, the study found that, though the frequency of communication between first-generation and non-first-generation students did not significantly differ, first-generation students reported the communication to be lower in helpfulness and quality. The quality of the communication was positively associated with students' first year GPAs (Palbusa & Gauvain, 2017).

Financial Resources

A second barrier is college costs and a lack of access to financial resources. College tuition is a significant barrier to college access since tuition has increased over time, while family incomes have remained stagnant for over a decade. Furthermore, obtaining financial aid requires having insight and information about the process, such that many students who would qualify for aid fail to access funding due to a lack of procedural knowledge. First-generation students in particular may come from households with fewer financial resources and greater financial constraints (Atherton, 2014; Bui, 2002; Choy, 2001; Inman & Mayes, 1999; Lee et al., 2004; McCarron & Inkelas, 2006; Terenzini et al., 1996). For example, two studies by Terenzini et al. (1996) and Bui (2002) find that first-generation students are more likely to come from lower socioeconomic backgrounds and have more dependents, indicating that first-generation college students have access to fewer financial resources and have greater financial responsibilities. Bui (2002) and Byrd & MacDonald (2005) additionally report that first-generation college students were more likely to report worrying about financial aid for college.

Academic Preparation

A third barrier to college access is academic preparation. College readiness is defined by American College Testing (ACT) as "the level of preparation a student needs to enroll and succeed—without remediation—in a credit-bearing general education course at a 2-year or 4-year institution, trade school, or technical school" (American College Testing (ACT), 2007, p. 5). Despite college preparation being a primary goal of most high schools in the country, the college readiness of many students is below standard (Cline et al., 2007; Moore et al., 2010).

Students from first-generation backgrounds may face added challenges to being academically prepared for college (An, 2013; Atherton, 2014; Collier & Morgan, 2007; Huerta & Watt, 2015; Hungerford-Kresser & Amaro-Jiménez, 2012; Reid & Moore, 2008; Warburton et al., 2001). First-generation students on average have lower grade point averages (GPAs) (Atherton, 2014; Lee et al., 2004), complete fewer rigorous high school courses (Choy, 2001; Terenzini et al., 1996), have lower scores on standardized tests (Atherton, 2014; Bui, 2002; Choy, 2001; Warburton et al., 2001) and lower cognitive skills as measured by reading, math, and critical thinking pretests (Terenzini et al., 1996), Lower levels of academic preparation may make it more challenging for first-generation students to enroll in the postsecondary institution of their choice or create lower academic aspirations. However, a rich body of literature has found that lower performing students who are strategically assigned to coursework, teachers, schools, or academic programs, or provided additional resources, may experience significant improvements in their academic preparation and accumulation of human capital (Burch et al., 2016; Darling-Aduana & Heinrich, 2018; Dougherty, 2016; Dougherty et al., 2017; Gershenson et al., 2017; Greenwald et al., 1996; Joshi et al., 2018).

Demographic Characteristics

First-generation students' demographic characteristics also have been found to be associated with their postsecondary outcomes. First-generation students are more likely to be female, older than traditional-aged college students, students of color, and have children (Bui, 2002; Inman & Mayes, 1999; Terenzini et al., 1996). A number of studies have found that first-generation students from particular demographics have lower postsecondary outcomes compared to their non-first-generation peers (Bui, 2002; Terenzini et al., 1996).

Differences in Outcomes for First-Generation Students

These challenges first-generation students encounter are associated with lower postsecondary outcomes in terms of access, opportunities during school, and degree completion. In terms of college access, a survey of first-generation and non-first-generation students in a southern state by Inman and Mayes (1999) finds that first-generation students are more constrained in the location of the institution they are able to attend, with many first-generation students reporting they would be likely to not attend any college if their location-based or scheduling needs were unable to be accommodated. First-generation students also may have lower quality experiences while enrolled. A prominent study by Terenzini, Springer, Yaeger, Pascarella and Nora (1996) found that first-generation students took fewer humanities and fine arts courses, took fewer credit hours in their first year, were less likely to be in an honors program, studied for fewer hours, worked more hours off campus, and reported more on-campus discrimination.

With respect to persistence and degree completion, scholarship on first-generation student finds that these students are less likely to persist and complete a degree compared to their non-first-generation peers. An event history analysis examining first-generation students' college attrition finds that first-generation students from low income backgrounds or who had low high school performance were significantly more likely to leave the institution than similar non-first-generation students (Ishitani, 2006). Correspondingly, a recent report by the U.S. Department of Education (2017) finds that a higher percentage of first-generation students than continuing-generation students who did not complete their degree reported college affordability as the reason for leaving.

While current work typically examines outcomes such as graduation, persistence, or degree attainment using nationally representative or local, institution-level data (Cragg, 2009; Fike & Fike, 2008; Ishitani, 2003, 2006, 2016; Nunez & Cuccaro-Alamin, 1998; Redford et al., 2017; Toutkoushian et al., 2019; Warburton et al., 2001), less work has been conducted analyzing students' short-term outcomes leading towards graduation. Only two studies examine credit outcomes, including credits attempted and earned for varying definitions of first-generation students. A study by Pascarella and colleagues (2004) investigates net differences in first-generation and non-first-generation students' academic and nonacademic college experiences. Using a sample of 1,518 student observations obtained from national survey data from 1992, Pascarella and colleagues (2004) group credit hours earned in students' second or third year with other variables such as hours studied or worked, finding no significant difference between first-generation and non-first generation students.

D'Allegro and Kerns (2010) use descriptive means and ordinary least squares regression to observe the difference between credits earned and attempted using survey data of 2,437 first-time, first-year students enrolling at a four-year institution during 2000-2006. While the analysis focuses on the amount of variation explained by precollege predictors in the OLS models and comparing means using t-tests, the authors observe that students whose parents have greater college experience attempt and earn more credits, though differences appear modest. These analyses are limited in scope, as the sample sizes are small, and neither analysis incorporates students' financial resources, which are a vital component of students' success. As credits attempted and earned are predictors of student retention and graduation, it is important to continue to examine these outcomes to document at a more granular level where students may struggle (Adelman, 1993, 2006; D'Allegro & Kerns, 2010; Ishler & Upcraft, 2005).

While some studies incorporate financial resources and academic preparedness as control variables (Atherton, 2014; Cragg, 2009; Fike & Fike, 2008; Inman & Mayes, 1999; Johnson, 2008; Padgett et al., 2012; Redford et al., 2017; Terenzini et al., 1996; Toutkoushian et al., 2019), studies have not examined heterogeneity in outcomes based on students' differential access to human capital. As such, there remains a need to systematically assess varying definitions of first-generation status, documenting differences in students' early credit attainment. Observing variation amongst different groups of first-generation students may shed light on how parents share information about college with their children, specifically with respect to the passage of cultural and social capital (Toutkoushian et al., 2018, 2019).

Empirical Strategy

Data

This project uses a unique Tennessee administrative dataset obtained through the Tennessee Postsecondary Evaluation and Analysis Research Lab (TN-PEARL), a research-practice partnership between Vanderbilt University's Peabody College of Education, the University of Tennessee's Boyd Center for Business and Economic Research, and the Tennessee Higher Education Commission (THEC). The dataset is housed at P20 Connect Tennessee (P20), the state's longitudinal data system. Data contain longitudinal information on students who enroll in Tennessee public community colleges and four-year universities from 2010/11 through 2017/18[13], including student demographics, detailed, term-level information on postsecondary

[13] In this study, the leading year is used to represent school year. So, "2017" would represent the 2017/18 academic year.

enrollment, eligibility for financial aid, family financial resources from the FAFSA, and students' precollege test scores.

Sample

The analytic sample includes eight cohorts of first-time, first-year students who first enroll in Tennessee community or four-year colleges in the 2010/11 through the 2017/18 school years, who have filed a FAFSA, are Tennessee residents, who are dependents, and who have complete information on the outcome and explanatory variables of the study.[14] Restricting the analysis to include only students who file the FAFSA was necessary to identify students' first-generation status and available financial resources.[15] The analysis was also restricted to in-state students who are dependents, as financially independent and non-resident students who have the means to attend an out-of-state institution were not in the study's population of interest of traditional first-time, first-year students. First-time, first-year students were identified using a pre-existing indicator variable in the P20 data.[16] This results in a sample of 189,358 observations capturing information on students' first-term of enrollment.

[14] Students with complete information on enrollment, but who do not attempt any credits, were removed from the sample.

[15] Since FAFSA filers may be different than non-FAFSA filers, it is important to examine differences in these students' characteristics. Appendix Table A2-1 shows the demographic characteristics and academic preparedness of students who do and do not file the FAFSA. Students filing the FAFSA were more likely to be female, less likely to be White, and more likely to be Black compared to those who do not file. Students who file the FAFSA also have higher ACT scores and are less likely to have a missing ACT score (indicating they are more likely to take the test). The main difference is that FAFSA filers have lower academic preparedness than non-FAFSA filers and are more likely to be students of color, which could also indicate a lack of other resources and supports. Since only students who file the FAFSA are included in this analysis, this selection could influence the outcomes observed.

[16] Some students in the data were high school students participating in the dual-enrollment program in which they took college-level coursework during high school. For these students, dual-enrollment terms were removed such that their first time in the data was during the semester they first enrolled following high school graduation. Finally, some students' first-term of enrollment was summer in which students enrolled part-time. These summer terms were treated similar to dual-enrollment. These summer terms were omitted such that a students' first-term of enrollment was either a fall or spring term. In total, about 4,000 observations were omitted for 1,000 unique students.

Measures

Independent Variable

The FAFSA asks families to provide the highest level of schooling completed by both parents. Families select from the following options: (1) Middle school/Jr. High, (2) High School, (3) College or beyond, or (4) Other/unknown. Using this information, three measures of parental education were created. First, students' first-generation status was operationalized using a binary indicator equal to one when a student had at least one parent who had not completed a college degree (college or beyond). This indicator represents students who do not come from households where both parents have college-going capital. The other/unknown category was treated as non-college-going.[17]

Next, to measure the relationship between levels of parental capital and students' first-term outcomes, the above binary indicator was separated into two additional measures. The second measure of first-generation status contains three categories: students with two degree-holding parents, students with only one degree-holding parent, and students with no degree-holding parents. This measure provides for the estimation of increased access to parental capital around college. The third measure breaks down the categories further still into four categories: students with two degree-holding parents, students for whom only their mother has a college degree, students for whom only their father has a college degree, and students with no degree-holding parents. This measure provides for the estimation of both increased access to parental capital as well as access to parental capital from a particular parent.

[17] Of the 189,358 observations in a student's first term of enrollment, the highest education level was unknown for 6 percent of fathers and 9 percent of mothers.

Dependent Variables

The primary dependent variables in this study are students' first-term credits attempted, first-term credits earned, percent credits earned of those attempted, and first-term GPA. Credits attempted and earned are continuous measures of credits. Percent credits earned is calculated by dividing credits earned by credits attempted.[18] GPA is a continuous measure of GPA points.

In addition to earning credits during their first term, students may also have earned credits prior to their first term of enrollment through dual enrollment, Advanced Placement, or International Baccalaureate programs during high school, or summer programs. To examine differences in these pre-enrollment opportunities, dependent variables for cumulative credits attempted and earned, percent credits cumulatively earned of those attempted, and cumulative first-term GPA are also used. These variables measure students' total credit and GPA attainment by the end of their first-term of enrollment.

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[18] Modeling dependent variables as percentages should be done with caution (Wooldridge, 2012). A percent variable has a binomial distribution, as it measures the percent credits successfully earned out of those attempted. However, such a percent is likely non-linear in the extremes, especially since the range of the variable includes values in the tails (typically, below 20 and above 80 percent). Furthermore, a percent is bounded from 0 to 100 percent, which violates an assumption of linear regression models, namely that the outcome variable is unbounded (Wooldridge, 2012).

Another way to model the percent credits earned variable is to include as the dependent variable the number of credits earned and adjust the outcome by controlling for the number of credits attempted. All tables and figures were estimated replacing the percent credits earned variable with a model predicting term credits earned and adjusting for credits attempted. As an example, main analyses estimating term credits earned (Table 2-3 and Table 2-4) are compared with models predicting term credits earned while adjusting for term credits attempted (Appendix Table A2-2 and Appendix Table A2-3). Neither the significance nor the direction of the estimates changed in any way after changing the percent variable to a model estimating credits earned while conditioning on credits attempted. In most cases, results on coefficients of interest for both the percent and adjusted credits earned models are null. As results were indistinguishable in sign and significance and are mostly null, the percent variable was chosen to include in the main results as it may be intuitive for some readers to think about credits earned as a percent rather than as conditional on credits attempted.

Control Variables

This study uses four groups of control variables identified in prior literature as related to students' college success, including students' demographic characteristics, level of academic preparedness, access to financial resources, and institutional characteristics.

Demographic Characteristics. Student demographic characteristics include students' race, sex, and citizenship status. Student race is a categorical variable for whether a student is Black, White, Latinx, Asian, or Other race/ethnicity. Student sex is a binary indicator equaling 1 when a student is female and 0 if male. Citizenship status is a binary indicator equaling 1 when a student is a U.S. citizen and 0 if they have a temporary or permanent visa.

Academic Preparedness. Students' academic preparedness captures the academic skills students may have when navigating college and completing collegiate work, such as level of academic readiness, time management skills, motivation, or maturity. Academic preparedness is measured using students' ACT composite score, whether students were ever dual enrolled in postsecondary coursework during high school, whether a student earned any Advanced Placement (AP) credits during high school, and students' age when they first enrolled as first-time, first-year students. ACT composite score is a continuous variable ranging from 1 to 36.[19] Dual enrollment is a binary indicator equal to 1 if a student ever dual enrolled in college coursework during high school and 0 otherwise. Earning AP credits is an indicator equaling one if a student earned any Advanced Placement credits during college.[20] Age of first enrollment is a categorical variable for whether a student enrolled for the first time at age 17, at age 18, or

[19] While all variables have some degree of missingness, the ACT composite score, a key measure of students' academic preparedness for college, has a relatively low level of missingness. The classes of 2017 and 2018 had access to retake the ACT test for free. Additionally, the ACT become a required test for high school graduation for the graduating class of 2018 (Tennessee Department of Education, 2019)

[20] Since a very small percentage of students in the data earn AP credits in high school, AP credits earned was modeled as a binary rather than a continuous variable.

between 19-24. Most first-time, first-year students enroll between at around age 18-19, but some students in the sample enrolled younger or older than the traditional age.

Financial Resources. Students' access to financial resources is measured using data from the FAFSA form, which provides information on students' access to family resources and their eligibility for various federal and state awards and scholarships. Family resource variables include parental expected financial contributions (EFC) towards postsecondary education and students' and parents' adjusted gross income (AGI). Parental EFC is calculated using a formula delineated by the U.S. federal government. This formula considers household size, and parental income, work status, savings, and investments. Households may have an EFC of zero if household income falls below a certain threshold.[21] AGI is reported using information from federal tax forms and includes wages, alimony, Social Security, and business income. Parent and student AGI and parental EFC were log transformed to ease interpretation. In a minutia of cases, students or parents had negative incomes or incomes of 0. A negative AGI indicates that individuals experienced financial losses greater than their total yearly income. Since the natural log function is only defined for values greater than 0, values of 0 for parental EFC and parent and student AGI were replaced by 1.

Additionally, binary indicators for students' eligibility for frequently accessed federal- and state-level scholarships and grants were also included. These include measures for whether a student was eligible for the Pell Grant, the Tennessee Student Assistant Award (TSAA), the Tennessee HOPE scholarship, the HOPE Access grant, the Tennessee HOPE Aspire award, and the General Assembly Merit (GAM) scholarship. These indicators denote eligibility, and not necessarily take-up, of the award. The Pell Grant is a federal grant that is awarded to students

21 See here for the EFC formula guide.

who meet the government's basic eligibility criteria, amongst other financial, school, and family factors.[22] The TSAA is a state needs-based award for eligible Tennessee high school students. The Tennessee HOPE scholarship is a merit-based scholarship for eligible Tennessee high school students. The Tennessee HOPE Aspire award is awarded to students who are eligible for the Tennessee HOPE scholarship and who have an income less than $36,000. The Tennessee HOPE Access grant is a merit-based scholarship for low-income students who just miss the HOPE scholarship criteria. The GAM is an additional merit-based scholarship that supplements the HOPE scholarship for high-achieving entering first-year students.[23]

Institutional Characteristics. To control for differences in student performance, professional goals, and other institution-related factors that may affect student outcomes, institution and major fixed effects are included. Heterogeneity in student outcomes due to institution of enrollment and major may arise from differences in the required coursework, number of credits, and institutional resources, as well as differences amongst students who choose particular institutions or majors, such as level of rigor, tuition, or geographic distance to home. Students' institution is the public institution of enrollment in their first term. Students in the sample attend one of 22 Tennessee public two- or four-year institutions in their first term. Anywhere from 1.7 percent (approximately 3,000 students) to 12.15 percent (approximately 23,000) of students in the analytic sample attend a given institution during their first term. Students' major is a categorical variable of students' currently declared major in their first term of enrollment. This variable was created by categorizing over 280 major codes into 7 common areas of study.[24]

22 For more information on needs-based awards, visit the following sites: Pell Grant, TSAA.
23 For information on the Tennessee HOPE scholarships, visit the following sites: HOPE, Aspire, Access, GAM.
24 First, major CIP codes were grouped into 32 categories using pre-existing identifiers for major. Next, the 32 major categories were collapsed into 7 common areas of study (e.g. liberal arts, business, health, etc.).

In addition to institution and major fixed effects, controls are included to capture students transition to college and type of enrollment. These include an indicator for seamless enrollment in the fall following high school graduation, as well as an indicator for full time enrollment, equaling one when a student attempted at least 12 credits during a term.

Sample Characteristics

Figure 2-1 presents the distribution of first-generation students in the sample by level of parental education. Of the 189,358 in the sample, 35.1 percent are non-first-generation and 64.9 are first-generation. 36.3 percent of students come from households where neither parent completed college and 28.7 percent of students have at least one parent who has completed college. Table 2-1 presents descriptive characteristics of students during their first term of enrollment. Column 1 shows characteristics for students with no degree-holding parents, while columns 2 and 3 show characteristics for students with one or two degree-holding parents, respectively. Column 4 shows the sample average and columns 5 and 6 show the minimum and maximum values of each variable in the sample.

First-generation students with no or one degree-holding parent are more likely to be Black, Latinx, or Asian, less likely to have dual enrolled during high school, and have lower ACT scores than their non-first-generation peers. First-generation students have slightly higher incomes than their non-first-generation peers, indicating that these students may be more likely to work during high school, and have fewer family resources (i.e. parental income and EFC) when transitioning to college. First-generation students are also more likely to be eligible for needs-based grants, such as the Pell Grant and the TSAA, and are less likely to be eligible for merit-based scholarships such as the HOPE Scholarship. In terms of institutional characteristics, first-generation students are more likely to enroll in a community college in their first term compared to their non-first-generation peers and are slightly more likely to declare a health or medicine major. They are also less likely to seamlessly enroll.

Table 2-2 compares the mean characteristics for students across all outcome variables. First-generation students attempt and earn more credits in their first, with first-generation students earning about 1 fewer credit, and complete a greater percent of credits attempted. Non-first-generation students also earn lower GPAs than their non-first-generation peers. Cumulatively, first-generation students attempt about 1 fewer credit and earn 2 fewer credits.

Analytic Strategy

The aim of this analysis is to obtain an unbiased estimate of the difference between first-generation and non-first-generation students' first-term credit attainment outcomes. As this analysis relies on nonexperimental data in which the assignment of students to institutions and courses of study is non-random, the analysis must account for nonrandom selection and sorting of students. To do this, this analysis uses a fixed-effects strategy. The primary benefit of using fixed effects as a within-estimator is to leverage variation amongst students within each institution, major, and school-year to account for the sorting of students to individual institutions. Students' reasons for attending a particular institution as well as the sources and supports they receive once enrolled are expected to play a role in students' credit accumulation. In addition to the institution students attend, students' academic outcomes may also be shaped by their demographic characteristics, level of academic preparedness, and access to financial resources.

To examine the relationship between first-generation student status and students' first-term outcomes, the following model is estimated:

$$Y_{ijmt} = \beta_0 + \beta_1 FirstGen_{2i} + \beta_2 D_i + \beta_3 A_i + \beta_3 F_i + \beta_4 W_i + \gamma_j + \tau_m + \eta_t + \epsilon_{ij} \quad (1)$$

Where Y_{ijmt} is a given credit or GPA attainment outcome for student i enrolled in institution j enrolled in major m in school year $t. FirstGen_{2i}$ is a binary variable equaling one when a student has at least one parent who has not completed a college degree. β_1 is the coefficient of interest and represents the average change in students' credit or GPA attainment resulting from students' status as a first-generation college student. D_i is a vector of demographic characteristics, including student race, sex, and citizenship status. A_i is a vector of academic preparedness, including students' ACT composite score, indicators for whether the student dual enrolled in high school and earned AP credit in high school, and indicators for whether the student was older or younger than traditional age at the time of enrollment. F_i is a vector of students' access to financial resources, including students' and parents' AGI, parental EFC, and students' eligibility for the Pell Grant, the TSAA, or one of four Tennessee HOPE scholarships. W_i is a vector of coefficients for seamless and full time enrollment. γ_j, τ_m and η_t represent institution, major, and school year fixed effects, respectively, each differencing out characteristics unique to each institution, major, or school year. Finally, to account for correlations between the idiosyncratic error terms for observations within a given institution, standard errors are clustered at the institution level.[25]

[25] Standard errors are typically clustered when the observations are not expected to be independent and identically distributed (i.i.d) and are correlated within clusters. However, when fixed effects are also included in the model, the motivation to cluster standard errors is less clear. Scholars like Abadie et al. (2017) and Cameron and Miller (2015) argue for the use of clustered standard errors in a fixed effects model "if either the sampling or assignment varies systematically with groups in the sample" (Abadie et al., 2017, p. 2).

Furthermore, scholars hold that the addition of fixed effects only partially accounts for within-cluster correlations in the error terms, again, making the case to cluster standard errors (Cameron & Miller, 2015). In the present study, assignment to institutions is not random, and both institution and major fixed effects are used, indicating support for the use of errors clustered at the institution level, the level at which a relationship between error terms is expected. However, Abadie et al. (2017) also argue that clustering when using fixed effects matters only if there is heterogeneity in treatment effects (i.e. first-generation status) (p. 14). As there is some observed heterogeneity in first-generation status, this paper presents the more conservative cluster-robust standard errors in the main analyses.

All tables were also re-estimated using Huber-White standard errors. In these models, coefficients appear significant at more conservative thresholds, and differences between groups appear significant, as examined by tests of

To examine variation in the relationship between students' first-generation status and students' credit and GPA outcomes, the binary indicator $FirstGen_{2i}$ is replaced by two indicators, $FGNoCollege_i$ and $FGOneCollege_i$, which represent first-generation students with no degree-holding parents or those with one degree-holding parent, respectively:

$$Y_{ijmt} = \beta_0 + \beta_1 FGNoCollege_i + \beta_2 FGOneCollege_i + {}_i \qquad (2)$$
$$\beta_3 D_i + \beta_4 A_i + \beta_5 F_i + \beta_6 W_i + \gamma_j + \tau_m + \eta_t + \epsilon_{ij}$$

The coefficients on β_1 and β_2 represent the average difference in credit and GPA attainment for first-generation students with no degree-holding parents and first-generation students with one degree-holding parent, respectively, compared to the reference category of non-first-generation peers with two degree-holding parents. Tests for the equality of regression coefficients (Wald tests) compare the probability that the coefficients for both groups of first-generation students are equal. Changes in the magnitude and significance of coefficients between groups indicate how greater access to parental capital affects students' credit attainment.

To further analyze the relationship between parental capital and students' first-term outcomes, the indicator for first-generation students with only one parent with a college degree ($FGOneCollege_i$) is replaced by two indicators, $FGMomCollege_i$, and $FGDadCollege_i$, representing students for whom only their mother or only their father has a college degree, respectively:

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regression equivalence. As an example, main analyses from Table 2-3 and Table 2-4 are shown with Huber-White standard errors in Appendix Table A2-4 and Appendix Table A2-5.

$$Y_{ijmt} = \beta_0 + \beta_1 FGNoCollege_i + \beta_2 FGMomCollege_i + \beta_3 FGDadCollege_i + \beta_4 D_i + \beta_5 A_i + \beta_6 F_i + \beta_7 W_i + \gamma_j + \tau_m + \eta_t + \epsilon_{ij} \quad (3)$$

The three coefficients β_1, β_2, and β_3 now represent the difference between each of the three categories of first-generation student, namely, students with no degree-holding parents, students where only their mother has a college degree, and students where only their father has a college degree. The reference category remains non-first-generation students with two degree-holding parents. As above, Wald tests compare whether the coefficients β_1, β_2, and β_3 are significantly different from one another.

Finally, to examine the extent to which the relationship between students' first-generation status and students' first-term attainment varies by students' access to financial resources and students' level of academic preparedness, interaction terms are sequentially added to Model 1 interacting a given financial resource with the binary indicator for students' first-generation status, $FirstGen_{1i}$. The financial resources interacted are parental AGI and parental EFC. A similar interaction term between students' ACT composite score and their first-generation status is also examined. For instance, the model interacting parental AGI with first-generation status can be written as follows:

$$Y_{ijmt} = \beta_0 + \beta_1 FirstGen_{1i} + \beta_2 (FirstGen_{1i} * ParentAGI_i) + \beta_3 D_i + \beta_4 A_i + \beta_5 F_i + \beta_6 W_i + \gamma_j + \tau_m + \eta_t + \epsilon_{ij} \quad (4)$$

Here, the coefficients of interest include the coefficient on first-generation status β_1, the coefficient on the interaction β_2, and the coefficient for parental AGI, captured in the vector β_5. The interaction term β_2 represents the estimated marginal difference in credit or GPA attainment between first-generation and non-first-generation students from a one unit increase in the log of parental AGI.

Limitations

This study is not without limitations. There may be additional characteristics of students beyond those included in this study that relate to students' postsecondary outcomes such as students' neighborhood of residence, access to information on college-going from siblings or other family, and goals and expectations around college. Some of these unobservable factors may be endogenous, influencing both performance in college as well as selection into a postsecondary institution. While this analysis cannot measure and account for how these factors may have influenced students' postsecondary outcomes, it attempts to proxy for factors that may affect student outcomes by including a broad range of controls utilizing the rich data available in the P-20 data system.

Additionally, survivor bias is a concern, as the study only has data on students who ultimately enroll in college. Since first-generation are much less likely to enroll in college (Cataldi, 2018), this sample likely contains higher performing first-generation students who were able to successfully enroll in college, despite facing challenges during the transition. Findings from this study should be interpreted in context of this sample selection. Even amongst first-generation students who successfully enroll and are likely higher achieving, this analysis finds gaps in their college achievement as early as their first term of enrollment, after accounting for differences in their financial resources, academic preparedness, demographics, and institution of enrollment.

Statement of Researcher Positionality

I would like to make a brief note about researcher positionality in the context of this study. While I am not a first-generation college student in the traditional sense, I am a child of immigrants. It was challenging to navigate the American school system, especially the transition to college. As such, this study resonates with my own childhood experiences trying to navigate the complicated process. Furthermore, my experiences as a teacher for students primarily from immigrant families have helped me understand the challenges associated with navigating an unfamiliar school system. These experiences motivate me to better support first-generation children who may experience barriers to accessing postsecondary education. Given my long-term research interests in supporting socially significant and traditionally underserved student populations, I am deeply invested in making sure this work is relevant, timely, and policy-driven.

Results

Using an institution fixed effects strategy, this analysis finds that, *ceteris paribus*, first-generation attempt and earn fewer credits than non-first-generation students and have lower GPAs. Stratifying the definition of first-generation students reveals that first-generation students with one degree-holding parent perform slightly better than first-generation students with no degree-holding parents. Stratifying the definition of first-generation students even further shows some differences amongst first-generation students whose father has a college degree and first-generation students for whom only their mother has a degree or neither parent has a college degree. Heterogeneity analyses find few differences in the marginal difference for first-generation and non-first-generation with differential academic preparedness and financial resources. Positive marginal differences were observed for first-generations students who have higher ACT scores and who have parents with higher parental AGI in terms of cumulative credits earned and percent term credits earned, respectively, suggesting that students with greater resources are better able to access educational opportunities for postsecondary credit attainment prior to their first term. Findings for each research question are discussed in detail below.

RQ1: What is the relationship between students' first-generation status and their first-term credit attainment and GPA?

Table 2-3 reports estimates from models estimating the relationship between the binary indicator of students' first-generation status and students' first-term outcomes. Columns 1-4 report results for the number of credits attempted and earned in the first term, the first term GPA, and the percent credits earned in the term out of those attempted. Columns 5-8 report results for outcomes measured for the cumulative number of credits and cumulative GPA. First-generation students within the same institution, major area of study, and school-year, and with similar demographic characteristics, level of academic preparedness, and similar access to financial resources, attempt, on average, 0.05 fewer credits and earn 0.22 fewer credits in their first term, compared to their non-first-generation peers. When adjusting for the number of credits attempted, the percentage of credits first-generation students earn is 1.26 percentage points lower than that of their non-first-generation peers. First-generation students also have GPAs that are 0.07 points lower in their first term compared to non-first-generation students. When examining cumulative credits earned, there is no statistical difference in the cumulative credits attempted between first-generation and non-first-generation students. Still, first-generation students who are similar in their academic preparedness and participation in dual-enrollment programs, earn on average 0.22 fewer credits than their non-first-generation peers, have lower cumulative GPAs, and complete fewer credits attempted.

Figure 2-2, Panels A and B illustrate how much variation in the estimates is explained by different explanatory variables. Beginning with the naïve estimate of first-generation status on a given outcome, each subsequent model adds controls. The figure shows shifts in the coefficient on the binary indicator for first-generation status with each additional group of covariates, as well as the shift in the 95 percent confidence interval. A larger shift in the magnitude of the estimated coefficient and a decrease in the span of the confidence interval from the addition of a new group of variables suggests that the variable group explains a larger proportion of the variation in the dependent variable. The addition of the demographic characteristics of sex, race, and citizenship status do not markedly shift the magnitude of the coefficient or the span of the confidence interval. However, the addition of financial and academic characteristics changes the magnitude of the estimated coefficients as well as the span of the 95 percent confidence interval, suggesting that these two groups of variables explain a greater proportion of variation in students' first-term credits and GPA than demographics. The addition of major and institution fixed effects explains additional variation. Examining the change in the adjusted R^2 from the estimated models further illustrates these findings.

RQ2: How does this relationship vary based on levels of parental education?

Variation in the Level of Parental Education

The next set of analyses examine variation for students with different levels of parental capital. Panel A of Table 2-4 presents results for models estimating the relationship between first-generation students who have one or no degree-holding parents and their first-term outcomes. Regarding term credits in columns 1-4, both groups of first-generation students attempt and earn fewer credits than their non-first-generation peers and have lower GPAs. For example, first-generation students with no degree-holding parents attempt 0.06 fewer credits and earn 0.24 fewer credits than their non-first-generation peers. Moreover, coefficients for first-generation students with no degree-holding parents are lower in magnitude than those for first-generation students with one degree-holding parent. For instance, first-generation students with one degree-holding parent attempt 0.04 fewer credits and earn 0.197 fewer credits than their non-first-generation peers. A Wald tests suggests that the difference between the coefficients for students with no degree-holding parents and one degree-holding parent are only significant for term credits attempted.

When looking at cumulative credits earned, columns 5-8 reveal that first-generation students with no degree-holding parents earn cumulatively fewer credits by their first term compared to non-first-generation students. Wald tests also suggest that these students attempt and earn significantly fewer credits by their first term than first-generation students with one degree-holding parent. While similar to one another, first-generation students with no and one degree-holding parent have lower cumulative GPAs and earn a smaller percentage of credits attempted then their non-first-generation peers.

Variation in Which Parent Holds a Degree

Panel B of Table 2-4 presents results from models estimating the relationship for three groups of first-generation students, specifically inspecting which parent has the college degree for students with only one degree-holding parent. As above, significant, negative coefficients are observed for all groups of first-generation students across all four measures of term credits and GPA measures, though no significant relationship is observed for first-generation students for whom only their father has a college degree with respect to term credits attempted. Wald tests of coefficient equivalence note significant differences in students with no degree-holding parents and students for whom only their father holds a degree.

Considering credits earned as an example, these results suggest that students with no degree-holding parents earn 0.24 fewer credits in their first term than their non-first-generation peers. Students for whom only their mother has a degree earn 0.23 fewer credits, but there is no difference in the credits earned by students with no degree-holding parents and students for whom only their mother has a degree. Students for whom only their father has a degree earn 0.167 fewer credits than their non-first-generation peers and earn more credits than students for whom neither parent has a degree and more credits than students for whom only their mother has a degree.

Columns 5-8 present results for cumulative credits earned by students first term. There do not appear to be significant differences in first-generation and non-first-generation students in terms of the cumulative number of credits attempted by their first term. Students for whom neither parent has a degree and students for whom only their father has a degree earn fewer credits than non-first-generation students. Estimated coefficients for these two groups are not significantly different than one another. All groups of first-generation students earn lower GPAs and a lower percentage of cumulative credits attempted than non-first-generation students.

By and large, examining variation across parental level of education suggests that students who have more access to parental capital fare somewhat better than students with little to no access to parental capital. Results examining which parent holds a degree suggest there may be variation in outcomes, though significant estimates could also be a function of omitted variable bias, as considered in the discussion of the study.

RQ3: To what extent does the relationship between students' first-generation status and students' first-term attainment vary by students' access to financial resources and level of academic preparedness?

Next, the analysis presents findings from models estimating heterogeneity in first-generation students' first term outcomes for covariates capturing three key predictors of college success for students: (1) their level of academic preparedness, measured by students' ACT composite score, and their access to financial resources, measured by (2) parental adjusted gross income, and (3) parental expected financial contribution. As academic preparedness and financial resources have been linked with the extent to which students are able to succeed in college, it is important to examine potential differences amongst first-generation students based on variation in their academic preparedness and financial supports. In each of the three analyses of heterogeneity, both continuous and categorical measures for ACT composite score, parental income, and expected financial contribution were interacted with the binary indicator for first-generation student status. The omitted category in each interaction model is the category containing the mean ACT score, parental income, or expected financial contribution in the sample. Results examining heterogeneity across each of the three covariates are presented below.[26]

ACT Composite

Estimates examining heterogeneity with respect to students' ACT composite score are shown in Table 2-5. Of the eight outcomes examined, only two outcomes yield significant interactions between first-generation status and students' ACT composite score. The difference in the estimated relationship between first-generation and non-first-generation students for

[26] All results held even when other correlated measures of academic preparedness or financial resources were omitted from models (e.g. omitting parental income from models examining heterogeneity in parental EFC).

cumulative credits attempted and earned by their first term of enrollment from a one point change in their ACT composite score is 0.112 and 0.098, respectively. Figure 2-3 provides an illustration of the first estimate, showing the change in the marginal difference for first-generation students' cumulative credits attempted from a linear change in ACT composite score. Each point shows the marginal difference between first-generation and non-first-generation students at each ACT score. For students with low ACT composite scores, the marginal difference between first-generation and non-first-generation students is negative, suggesting that low performing first-generation students attempt fewer cumulative credits than their peers. For students with high ACT composite scores, the marginal difference is positive, suggesting that higher performing first-generation students may attempt more cumulative credits, though, these differences may not be significantly different from zero.

It is possible that the heterogeneous relationship between first-generation status and ACT score is non-linear. To further explore this possibility, Table 2-6 presents models in which ACT score is measured as a categorical variable. Here, the binary indicator of first-generation status is interacted with a categorical variable for ACT score percentiles. The reference category is students in the 25^{th} – 50^{th} percentile of ACT composite scores, representing scores of 19-21, often considered the minimum threshold for college readiness (Anderson, 2019). Positive and significant marginal differences are observed on the interaction term for first-generation students in the second highest quartile with respect to term credits earned (0.104) and percent credits earned (0.655) and in the topmost quartile with respect to cumulative credits attempted (1.063) and earned (0.957). Taking term credits earned for students in the second highest quartile as an example, calculating the predicted differences between student groups is a useful exercise. The significant, positive coefficient of 0.104 indicates that, when all other variables are held at their means, first-generation students in this ACT percentile are predicted to earn 11.66 credits as compared to their peers in the quartile below, who are predicted to earn 11.55 credits. As indicated by the model, this difference is statistically significant at the $p < 0.05$ level. No significant marginal differences are observed for models predicting GPA. Results from Tables 2-5 and 2-6 show that, while some heterogeneity is present with respect to students' academic preparedness, for the most part, differences in ACT score do not differentially affect first-generation students' first term academic performance.

Parental Income

Next, heterogeneity in financial resources is examined. Table 2-7 presents models with interactions between the indicator for first-generation status and the continuous, logged measure of parental income. Of the eight outcomes examined, only the model predicting percent term credits contained a significant interaction term. A positive, significant marginal difference of 0.091 is observed for first-generations with respect to percent term credits earned. In other words, a one percent increase in parental income for first-generation students is associated with a 0.01 percentage point increase in term credits earned relative to non-first-generation students. While statistically significant, the practical implications of this estimate to explain any differences in percent credits earned may be less meaningful.

To explore potential non-linearity in this relationship, the binary indicator of first-generation student status was interacted with a categorical variable for percentiles of parental income, shown in Table 2-8. The reference group is parental income between $60,000 - $100,000, which includes the mean income in the sample of $70,000. No significant interaction terms are observed for models estimating term-level outcomes. Positive, significant marginal differences are observed for the interaction terms for income levels in the top 50th percentiles for cumulative credits attempted (0.2 – 0.78) and earned (0.2 – 0.56). These differences translate into 0.002 – 0.01 percentage point differences from being in a higher income bracket. A negative, significant marginal difference is observed for the interaction term for students with parents in the top percentile of income with respect to cumulative GPA (-0.037). These interactions suggest that first-generation students whose parents have higher incomes are predicted to attempt and earn more cumulative credits than their first-generation peers of average income, but also earn lower overall GPAs. Again, while statistically significant, the practical implications of these findings may less meaningful.

Expected Parental Financial Contribution

Finally, heterogeneity in students' access to resource through parental expected financial contributions is examined. As with parental income, the binary indicator of first-generation status is interacted with a logged, continuous measure of parental expected financial contribution. Table 2-9 and 2-10 show parallel results for interaction models for the log of parents' expected financial contributions. Models using the continuous, logged measure of parental EFC in Table 2-9 find no significant marginal differences between first-generation and non-first-generation students with respect to any of the eight outcomes examined. Table 2-10 tests for potential non-linearity in this relationship, and models interactions between a categorical variable for percentiles of parental EFC, with the reference group as EFC between $6,000 and $21,000, containing the sample mean EFC of $16,000. Findings mirror those observed for models interacting the categorical variable of parental income in Table 2-8 above. No significant interaction terms are observed for models estimating term-level outcomes. Positive, significant marginal differences are observed for the interaction terms for EFCs in the top 50th percentiles for cumulative credits attempted and earned. Estimated coefficients are similar in magnitude as those in models containing interactions with parental income. These interactions suggest that first-generation students with parents with higher EFCs are predicted to attempt and earn significantly more credits than their first-generation peers, though the practical implications of these findings are again, likely negligible.

Overall, findings suggest little heterogeneity in the relationship between first-generation status and key factors related to college going. This suggests that, for term-level outcomes, first-generation students perform consistently lower than their peers, and that better academic preparation or financial resources makes little difference. Heterogeneity that was observed was concentrated amongst cumulative credits and cumulative GPA. As these variables capture opportunities that first-generation students would have accessed prior to their first-term of enrollment, that first-generation students with greater resources to access educational opportunities or supports is expected.

Robustness Checks

Next, robustness and sensitivity analyses test for (1) potential selection issues of students into the sample and (2) an alternate definition of first-generation status. In the section below, each threat to internal validity and the tests performed are discussed.

Sample Selection

A key concern is the selection of students into the sample who are inherently different from one another on unobservable characteristics. These differences may contribute to observed significant differences in first-generation and non-first-generation students. Students may differ based on their status as full-time or part-time students, whether they seamlessly enrolled in the fall immediately following high school graduation, their age at time of first enrollment, and their opportunity to dual enroll or take college coursework during high school through an AP or IB program. While some covariates may account for some of the differences (e.g. parental resources, ACT score, ever-dual enrolled), there are a host of unobserved characteristics that may not be captured using the covariates present in the data. They may have fewer financial resources, less academic preparedness, or other responsibilities outside of school such a job or family, which may limit their ability to enroll in a full course load of courses. To address this possibility, the main analysis tables, namely Tables 2-3 and 2-4, were re-estimated by removing each of the four groups above turn by turn. It should be noted that these variables are not highly correlated with one another (all correlations less than 0.2), as seen in Table 2-11, and thus represent unique characteristics of students in each category.

Full-Time Students. Since the analysis is limited to students under age 25, the analytic sample omits many part time students, who are typically older in age. Restricting the sample to full time students, i.e. those who attempt at least 12 credits in their first term, removes 9,362 student observations, or about 5 percent of the sample. As shown in Table 2-12, the exclusion of part time students yields estimates with the same sign and significance as those in the full sample in Table 2-3. However, estimates for term credits attempted and earned are slightly more negative than those in the full sample. In contrast, while still negative, estimates for term GPA and percent credits earned are slightly less negative than those in the full sample. There is no change in the estimate for cumulative credits earned, thought cumulative GPA and percent cumulative credits earned are similarly slightly less negative. When breaking down first-generation status into categories as shown in Table 2-13, the change in magnitudes of estimates follow an identical pattern when compared to estimates for the full sample in Table 2-4. Results from this robustness check indicate that, while part time first-generation students may attempt and earn fewer credits than their full time peers, their academic performance may be slightly higher.

Seamlessly Enrolling Students. Removing students who do not seamlessly enroll following high school graduation removes 21,180 students, or about 11 percent of the sample. Estimates shown in Table 2-14 are identical in sign and significance to those in Table 2-3, though slightly more negative in magnitude. A similar pattern is observed when examining variation within first-generation students (Table 2-15), though seamlessly enrolling first-generation students who have one degree-holding parents experience a slight improvement in term GPA when their non-seamlessly enrolling peers are excluded. This suggests that first-generation students who do not seamlessly enroll, all else equal, have slightly higher academic outcomes than their peers who do seamlessly enroll. First-generation students who seamlessly enroll and have one degree-holding parent may be better positioned to succeed academically, explaining the slight improvement in GPA.

Traditional Aged Students. While 18 is often thought of as the average age of a first-time, first-year student, students in the sample vary in age from 17 to 24, with about 55 percent of students being younger or older than traditional age. The vast majority of these students are older than the traditional age of 18 (54 percent). Restricting the sample to traditional age students removes 104,077 student observations. As shown in Table 2-16, results follow the pattern for full time and seamlessly enrolling students. Removing non-traditionally-aged students maintains the sign and significance of the estimates, though estimates for term credits attempted and earned are more negative in magnitude, while term GPA and percent credits earned are slightly less negative. The estimate for cumulative percent credits earned is also more negative in magnitude. These patterns persist when examination varying definitions of first-generation student status in Table 2-17, again suggesting that students who are older than traditional age may be better prepared or positioned to succeed academically, which explains the negative change in the magnitude of coefficients when these students are removed.

Never-Dual Enrolling Students. Finally, 23,175 students who dual enroll or earn AP credits are removed, representing 12 percent of the sample. As above, the removal of these students from the sample maintains the sign and significance of the estimates, though the magnitude is more negative, shown in Table 2-18 and Table 2-19. This intuitively makes sense, as first-generation students who are able to earn dual enrollment or AP credits prior to college enrollment are better prepared academically, explaining the decrease in magnitude of coefficients. However, students who may have taken some summer or winter coursework prior to enrolling in a fall or spring term were not excluded from the sample, as these opportunities go beyond what is offered through a traditional high school program. This would explain why the estimates on cumulative outcomes are non-zero and remain different than those on term-level outcomes.

Taken together, findings from this robustness check reveal that first-generation students who represent the average student—that is, students who enroll seamlessly and full time, do not dual enroll or earn AP credits, and who are traditional age—are lower performing than their counterparts. This is likely due to selection bias, as students who do not enroll seamlessly, do not dual enroll, enroll part time, or who are older than the average student may be different than traditional students. They may be more motivated, have greater resources, preparedness, or stability. Identifying these distinctions sheds light on the differences between key groups of students in the sample and helps explain how differences between students may affect both selection into the sample and subsequently, estimated outcomes.

Varying Definitions of First-Generation

The way first-generation students are defined varies across policies and studies (D'Amico & Dika, 2013; Ishitani, 2016; Terenzini et al., 1996; Warburton et al., 2001; Whitley et al., 2018). Studies have found that the way the definition is constructed matters, as results may vary when certain students are included or excluded from the intervention sample (Toutkoushian et al., 2019). Thus, a second concern is that findings from the study are a function of the way first-generation students are defined. To address this concern, the models in Table 2-3 were re-estimated using an additional indicator of first-generation status. The new binary indicator is equal to one when students have no degree-holding parents and zero otherwise. This more conservative definition of first-generation aligns with THEC's definition and categorizes students who have at least one degree-holding parent as non-first-generation (Tennessee Higher Education Commission, 2019a). These results provide a companion for results shown in Table 2-4 by changing the reference category from students with two degree-holding parents to students with at least one degree-holding parent.

As seen in Table 2-20, when defined more conservatively, first-generation students are still predicted to attempt (-0.04) and earn (-0.14) significantly fewer credits, earn lower GPAs (-0.038), and earn a lower percentage of their credits attempted (-0.72) than their non-first-generation peers. Coefficients are smaller in magnitude than those in Table 2-3, which show the estimates using the broader definition of first-generation students. Notably, the magnitude of the estimates for term- and cumulative-level outcomes are more similar to one another than in the results shown in Table 2-3. Results using the more conservative definition of first-generation show that students with no degree-holding parents, when compared to students with at least one degree-holding parent, are predicted to have slightly improved outcomes. This is likely due to the movement of students with one degree-holding parent, who have lower outcomes than their peers with two degree-holding parents, into the reference category. Findings reinforce the importance of carefully considering the definition of first-generation students, as the definition and comparison group have implications for how outcomes are estimated and interpreted.

Discussion

Since the passage of the Higher Education Act of 1965, greater attention has been paid to first-generation college students who are first in their families to attend postsecondary education. The aim of this analysis is to document gaps in first-generation students' first-term credit and GPA outcomes. Documenting these early gaps may signal lower outcomes for first-generation students in subsequent semesters or a higher likelihood of dropout or stopout. Additionally, this study measures how variation in access to parental capital is related to students' first-term credit and GPA outcomes, including an examination of which parent holds a college degree. This study also examines heterogeneity by students' access to financial resources and their pre-college academic preparation. Building on prior work, this study uses a longitudinal, state database containing detailed, term-level information on students enrolling in two- and four-year public colleges, to answer these questions.

Using an institution and major fixed-effects model that parses out variation between institutions and majors of study, this study finds that first-generation students differ from their non-first-generation peers in that they are more likely to be students of color, have lower levels of academic preparedness, come from lower resourced householders, and are more likely to enroll in a two-year institution. Controlling for these factors, similarly resourced first-generation students attempt and earn fewer credits than their non-first-generations peers in their first term and have lower GPAs. First-generations students also earn a lower percentage of credits attempted. When examining cumulative differences in credits and GPA, no difference is observed for the number of credits attempted. Yet, first-generation students earn cumulatively fewer credits by their first term and have lower cumulative GPAs, even after accounting for student dual enrollment, ACT score, and any AP credits earned, though the magnitude of the difference is quite similar to that on the coefficient for term credits earned.

Analyses breaking down the group of first-generation students by the number of parents that hold a college degree and by which parent holds a college degree demonstrate how access to greater parental capital by way of having degree-holding parents plays a role in first-generation students' first-term outcomes. While first-generation students attempt and earn fewer credits than their non-first-generation peers and have lower GPAs, students that have at least one degree-holding parent performed slightly better than students with no degree-holding parents. Nevertheless, Wald tests did not discern a significant difference in the magnitude of these coefficients between first-generation students in the two groups. These findings support the hypothesis that parents are better able to transfer information about college to their children if they themselves have completed college, since students who had at least one parent with a degree had slightly improved outcomes than those without.

There do appear to be differences in outcomes for first-generation students based on which parent has a college degree. While no differences were observed between students for whom neither parent has a degree and students for whom only their mother has a degree, Wald tests reveal statistically significant differences in the coefficients for first-generation students whose father has a college degree and other first-generation students. These finding could suggest that, even after accounting for other students personal and institutional attributes, students may be receiving more parental capital around college-going from their fathers than their mothers.

However, this finding is likely a function of gender-based differences in income and resources resulting from differences in education and labor force participation, omitted variable bias, or household structure. Tennessee is amongst the highest in the country in terms of the percent of children growing up in single-parent households, with a rate of 38 percent, 3 percentage points higher than the national average (Kids Count Data Center, 2018). Tennessee also has low female labor force participation and generally low bachelor's attainment (U.S. Department of Labor, 2018). As such, the analysis may suffer from omitted variable bias from a lack of information on parental education, the disproportionally lower rate of women who may hold postsecondary credentials for their work, and gender-differences in earnings. This combination of factors may make father's education more salient for students who enroll.

Tests reveal some heterogeneity in first-generation students' status and their access to financial resources, as well as their level of academic preparation. For most outcomes, interaction terms yielded null results, indicating that first-generation students perform consistently lower than their peers, with little differentiation between those with more financial resources or academic preparation. Significant interactions on cumulative credit and GPA variables supports the idea that students with greater resources are better able to access to educational opportunities for postsecondary credit attainment prior to their first term. Thus, for similarly positioned first-generation students who successfully enroll in college after accessing financial aid resources available to them, the primary barrier may be information and knowledge around navigating college rather than gaps in financial resources or level of academic preparedness.

A detailed examination of sample selection adds texture to this analysis by disentangling sources of variation in the group of students in the sample. In iteratively removing students who are different than the average student, i.e. those who enroll part time, those who do not seamlessly enroll, those who are younger or older than 18, and those who dual enroll in college, the analysis is able to examine how results change if these singular groups are excluded from the sample. It is important to remember that, when students are excluded, students in the reference group of non-first-generation students also changes.

In general, coefficients appeared to be the same sign and significance (negative), though estimates were more negative for term credits attempted and earned, and less negative for GPA. Students who remained in the sample were attempting and earning even fewer credits than their non-first-generation peers, but the differences in their GPAs relative to their peers decreased. In other words, while the gap in credits appears larger, the gap in achievement shrinks somewhat. This could be indicative of potential differences in the academic ability, resources, preparedness, or motivation of students in the groups excluded based on their first-generation status. For instance, students who enroll part time who are first-generation may be older or more motivated, and hence attempt or earn more credits than their peers who enroll full time. At the same time, they may also have more responsibilities, which may hinder their ability to score well academically. Differences once removing singular groups may also indicate that students who remain are more similar to one another academically, as could be the case with students who do not dual enroll in high school. While examining such differences is beyond the scope of the data available, findings from this exploration suggest that first-generation students are a nuanced and varied group, with unique needs, experiences, and skillsets.

Conclusion

Taken together, findings have two key implications. First, this study underscores findings from Toutkoushian and colleagues (2019), namely that access to parental capital matters. While all first-generation students face challenges once enrolled, students' first-term outcomes improved marginally when students had at least one parent with a college degree. To the extent that access to parental information and experience around college is a resource for students, it is noteworthy that students with one degree-holding parent still have lower first-term outcomes than students with two degree-holding parents. Building on the work of Toutkoushian et al. (2019), this study suggests that how first-generation students are defined matters, especially since students with one degree-holding parent, who are sometimes not included in the definition of first-generation students, have lower outcomes and would benefit from supports.

Second, policymakers may consider increasing supports for first-generation students earlier in the college application and enrollment process. While most prior studies examine rates of persistence or degree attainment, this study documents differences in not only pre-enrollment opportunities, as measured through cumulative credit and GPA outcomes, but also in first-term credit and GPA attainment. That differences amongst first-generation students arise early and are likely due to differences in access to information and social and cultural capital around college-going. As evidenced by analyses examining variation in level of parental education, even after controlling for a host of characteristics, first-generation students with access to some parental capital (i.e. one degree-holding parent), fared better in their first term. Further, aside from a few heterogenous differences, the study finds few differences amongst similar first-generation students across income or academic levels. This suggests that, conditional on enrollment, gaps in first-term credits are not explained by differential access to financial resources or greater academic preparedness in high school. Findings point to differences in information and know-how around college-going, as also documented by numerous studies.

Results from this study indicate that interventions are needed sooner for first-generation students. Prior work notes that first-generation students may benefit from greater access to academic and information supports to help them navigate the transition to college, as well as the throughout their terms of enrollment. Schools may consider providing students greater access to college counselors, who play a particularly important role in helping students navigate aspects of the college admissions process, such as academic perquisites, admissions testing, and paperwork (Avery et al., 2014). As noted by Fallon (1997), college counselors are in a position to help created targeted supports for first-generation college students by creating group guidance sessions for first-generation students only, helping then understand the importance of college, helping them think about college affordability, and make important decisions about course-taking and financial aid. Other supports may include peer and faculty networks, tutoring services, and academic guidance, which may be offered independently, or as wraparound services through programs like Nashville GRAD and Knox Promise (Adelman, 1993; Dennis et al., 2005; Ishitani, 2006; Orbe, 2004; Stephens et al., 2012).[27]

Given that differences in students' academic outcomes appear as early as students' first term of enrollment, first-generation students may also benefit from added supports once enrolled. Potential supports may include first-year seminars, faculty or peer mentors, or greater faculty awareness of the needs of first-generation students (Padgett et al., 2012). Policymakers may specifically consider offering resources and interventions during the semester that build students' informational and cultural knowledge around college-going, especially during the beginning

[27] For more information on these programs, visit: Nashville GRAD and Knox Promise.

terms of enrollment. In addition to first-year seminars that help students connect with faculty and peers, programs or peer mentors could help students become better connected with campus resources and organizations (Tobolowsky et al., 2017; Vaughan et al., 2014).

This study provides important and timely information on the landscape of first-generation students’ postsecondary attainment at a statewide scale. Unlike prior work, which typically focuses on enrollment, persistence, or degree attainment, the present study examines granular, first-term outcomes for students. In this way, results demonstrate that gaps in credit attainment begin as early as students’ first term of enrollment. Down the road, these small gaps may ultimately contribute to first-generation students lower rates of degree completion and persistence (Cataldi, 2018; Choy, 2001; Ishitani, 2016, 2006). As policymakers and universities seek to recruit and support first-generations in enrolling in college, it is important to support students not only when students are making the decision to enroll, but also during their semesters of enrollment. Future research is needed to further document term-level gaps between first-generation and non-first-generation students as they progress through their postsecondary schooling. Scholars may also study policies or interventions seeking to improve first-generation students’ access to information and social and cultural capital around college-going.

References

Abadie, A., Athey, S., Imbens, G., & Wooldridge, J. (2017). *When Should You Adjust Standard Errors for Clustering?* (No. w24003; p. w24003). National Bureau of Economic Research. https://doi.org/10.3386/w24003

Adelman, C. (1993). Insult, But No Injury: You Are Now a First-Generation College Student. *Educational Record; Washington*, *74*(1), 53.

Adelman, C. (2006). *The toolbox revisited: Paths to degree completion from high school through college.* (p. 223). U.S. Department of Education.

American College Testing (ACT). (2007). *Rigor at risk: Reaffirming quality in the high school core curriculum.*

An, B. P. (2013). The Influence of Dual Enrollment on Academic Performance and College Readiness: Differences by Socioeconomic Status. *Research in Higher Education*, *54*(4), 407–432. https://doi.org/10.1007/s11162-012-9278-z

Anderson, N. (2019, October 30). *Class of 2019 ACT scores show record-low college readiness rates in English, math*. The Washington Post. https://www.washingtonpost.com/education/2019/10/30/class-act-scores-show-record-low-college-readiness-rates-english-math/

Anyon, J. (1980). Social Class and the Hidden Curriculum of Work. *The Journal of Education*, *162*(1), 67–92.

Astin, A. W. (1975). *Preventing Students from Dropping Out* (1st edition). Jossey-Bass Inc Pub.

Atherton, M. C. (2014). Academic Preparedness of First-Generation College Students: Different Perspectives. *Journal of College Student Development; Baltimore*, *55*(8), 824–829.

Avery, C., Howell, J. S., & Page, L. C. (2014). *A Review of the Role of College Counseling, Coaching, and Mentoring on Students' Postsecondary Outcomes* (College Board Research Brief, pp. 1–15). College Board.

Barry, L. M., Hudley, C., Kelly, M., & Cho, S.-J. (2009). Differences in self-reported disclosure of college experiences by first-generation college student status. *Adolescence*, *44*(173), 55.

Bean, J. P. (1983). The Application of a Model of Turnover in Work Organizations to the Student Attrition Process. *The Review of Higher Education*, *6*(2), 129–148. https://doi.org/10.1353/rhe.1983.0026

Bills, D. B. (2003). Credentials, Signals, and Screens: Explaining the Relationship between Schooling and Job Assignment. *Review of Educational Research*, *73*(4), 441–469. JSTOR.

Bourdieu, P. (1977). Cultural reproduction and social reproduction. In J. Karabel & A. H. Halsey (Eds.), *Power and Ideology in Education* (pp. 487–511). Oxford University Press.

Bourdieu, P. (1986). The Forms of Capital. In A. Sadovnik (Ed.), *Sociology of Education: A Critical Reader* (2nd ed., pp. 83–95). Routledge Taylor & Francis Group.

Bui, K. V. T. (2002). First-generation college students at a four-year university: Background characteristics, reasons for pursuing higher education, and first-year experiences. *College Student Journal*, *36*(1), 3–11.

Burch, P., Good, A., & Heinrich, C. (2016). Improving Access to, Quality, and the Effectiveness of Digital Tutoring in K–12 Education. *Educational Evaluation and Policy Analysis*, *38*(1), 65–87. JSTOR.

Byrd, K. L., & Macdonald, G. (2005). Defining College Readiness from the Inside Out: First-Generation College Student Perspectives. *Community College Review*, *33*(1), 22–37. https://doi.org/10.1177/009155210503300102

Cameron, C. A., & Miller, D. L. (2015). A Practitioner's Guide to Cluster-Robust Inference. *Journal of Human Resources*, *50*(2), 317–372. https://doi.org/10.3368/jhr.50.2.317

Cataldi, E. F. (2018). *First-Generation Students: College Access, Persistence, and Postbachelor's Outcomes*. 31.

Choy, S. (2001). Students whose parents did not go to college: Postsecondary access, persistence, and attainment. In *National Center for Education Statistics, The condition of education.* (pp. xviii–xliii).

Cline, Z., Bissell, J., Hafner, A., & Katz, M.-L. (2007). Closing the College Readiness Gap. *Leadership*, *37*(2), 30–33.

Coleman, J. S. (1988). Social Capital in the Creation of Human Capital. In A. R. Sadovnik (Ed.), *Sociology of Education: A Critical Reader* (2nd ed., pp. 97–113). Routledge.

Collier, P. J., & Morgan, D. L. (2007). "Is that paper really due today?": Differences in first-generation and traditional college students' understandings of faculty expectations. *Higher Education*, *55*(4), 425–446. https://doi.org/10.1007/s10734-007-9065-5

Cragg, K. M. (2009). Influencing the Probability for Graduation at Four-Year Institutions: A Multi-Model Analysis. *Research in Higher Education, 50*(4), 394–413. https://doi.org/10.1007/s11162-009-9122-2

D'Allegro, M. L., & Kerns, S. (2010). Is There Such a Thing as Too Much of a Good Thing When it Comes to Education? Reexamining First Generation Student Success. *Journal of*

College Student Retention: Research, Theory & Practice, *12*(3), 293–317. https://doi.org/10.2190/CS.12.3.c

D'Amico, M. M., & Dika, S. L. (2013). Using Data Known at the Time of Admission to Predict First-Generation College Student Success. *Journal of College Student Retention: Research, Theory & Practice*, *15*(2), 173–192. https://doi.org/10.2190/CS.15.2.c

Darling-Aduana, J., & Heinrich, C. J. (2018). The role of teacher capacity and instructional practice in the integration of educational technology for emergent bilingual students. *Computers & Education*, *126*, 417–432. https://doi.org/10.1016/j.compedu.2018.08.002

Dennis, J. M., Phinney, J. S., & Chuateco, L. I. (2005). The Role of Motivation, Parental Support, and Peer Support in the Academic Success of Ethnic Minority First-Generation College Students. *Journal of College Student Development*, *46*(3), 223–236. https://doi.org/10.1353/csd.2005.0023

Dougherty, S. M. (2016). The Effect of Career and Technical Education on Human Capital Accumulation: Causal Evidence from Massachusetts. *Education Finance and Policy*, *13*(2), 119–148. https://doi.org/10.1162/edfp_a_00224

Dougherty, S. M., Goodman, J. S., Hill, D. V., Litke, E. G., & Page, L. C. (2017). Objective course placement and college readiness: Evidence from targeted middle school math acceleration. *Economics of Education Review*, *58*, 141–161. https://doi.org/10.1016/j.econedurev.2017.04.002

Dumais, S. A. (2002). Cultural Capital, Gender, and School Success: The Role of Habitus. *Sociology of Education*, *75*(1), 44–68. JSTOR. https://doi.org/10.2307/3090253

Engle, J. (2007). Postsecondary access and success for first-generation college students. *American Academic*, *3*(1), 25–48.

Fallon, M. V. (1997). The School Counselor's Role in First Generation Students' College Plans. *The School Counselor*, *44*(5), 384–393. JSTOR.

Field, J. (2016). *Social Capital* (3 edition). Routledge.

Fike, D. S., & Fike, R. (2008). Predictors of First-Year Student Retention in the Community College. *Community College Review*, *36*(2), 68–88. https://doi.org/10.1177/0091552108320222

Furquim, F., Glasener, K. M., Oster, M., McCall, B. P., & DesJardins, S. L. (2017). Navigating the Financial Aid Process: Borrowing Outcomes among First-Generation and Non-First-Generation Students. *The ANNALS of the American Academy of Political and Social Science*, *671*(1), 69–91. https://doi.org/10.1177/0002716217698119

Gershenson, S., Hart, C., Lindsay, C., & Papageorge, N. W. (2017). *The long-run impacts of same-race teachers*.

Gibbons, M. M., Rhinehart, A., & Hardin, E. (2019). How First-Generation College Students Adjust to College. *Journal of College Student Retention: Research, Theory & Practice*, *20*(4), 488–510. https://doi.org/10.1177/1521025116682035

Golann, J. W. (2015). The Paradox of Success at a No-Excuses School. *Sociology of Education*, *88*(2), 103–119. https://doi.org/10.1177/0038040714567866

Greenwald, R., Hedges, L. V., & Laine, R. D. (1996). The Effect of School Resources on Student Achievement. *Review of Educational Research*, *66*(3), 361. https://doi.org/10.2307/1170528

Huerta, J., & Watt, K. M. (2015). Examining the College Preparation and Intermediate Outcomes of College Success of AVID Graduates Enrolled in Universities and Community Colleges. *American Secondary Education*, *43*(3), 1–17.

Hungerford-Kresser, H., & Amaro-Jiménez, C. (2012). Urban-Schooled Latina/os, Academic Literacies, Identities: (Re)Conceptualizing College Readiness. *PennGSE Perspectives on Education Journal*, *9*(2), 14.

Inman, W. E., & Mayes, L. (1999). The importance of being first: Unique characteristics of first generation community college students. *Community College Review; Raleigh*, *26*(4), 3.

Ishitani, T. (2003). A longitudinal approach to assessing attrition behavior among first-generation students: Time-varying effects of pre-college characteristics. *Research in Higher Education*, *44*(4), 433–449.

Ishitani, T. (2006). Studying Attrition and Degree Completion Behavior among First-Generation College Students in the United States. *The Journal of Higher Education*, *77*(5), 861–885. https://doi.org/10.1080/00221546.2006.11778947

Ishitani, T. (2016). First-Generation Students Persistence at Four-Year Institutions. *College and University*, *91*(3), 22–33.

Ishler, J. L., & Upcraft, M. L. (2005). The keys to first-year student persistence. In M. L. Upcraft, J. N. Gardner, & B. O. Barefoot (Eds.), *Challenging & supporting the first-year student* (pp. 27–46). Jossey-Bass.

Johnson, I. (2008). Enrollment, Persistence and Graduation of In-State Students at a Public Research University: Does High School Matter? *Research in Higher Education*, *49*(8), 776–793. https://doi.org/10.1007/s11162-008-9105-8

Joshi, E., Doan, S., & Springer, M. G. (2018). Student-Teacher Race Congruence: New Evidence and Insight From Tennessee: *AERA Open*. https://doi.org/10.1177/2332858418817528

Kids Count Data Center. (2018). *Children in single-parent families in the United States*. https://datacenter.kidscount.org/data/tables/106-children-in-single-parent-families?loc=1&loct=2#detailed/2/2-53/false/37/any/430

Koestner, R., Franz, C., & Weinberger, J. (1990). The Family Origins of Empathic Concern: A Twenty-Six Year Longitudinal Study. *Journal of Personality and Social Psychology*, *58*(4), 709–717.

Lee, J. J., Sax, L. J., Kim, A. K., & Hagedorn, L. S. (2004). Understanding students' parental education beyond first-generation status. *Community College Review*, *32*, 1–20.

Lin, N. (2002). *Social Capital: A Theory of Social Structure and Action*. Cambridge University Press.

Martin Lohfink, M., & Paulsen, M. B. (2005). Comparing the Determinants of Persistence for First-Generation and Continuing-Generation Students. *Journal of College Student Development*, *46*(4), 409–428. https://doi.org/10.1353/csd.2005.0040

Martinez, J. A., Sher, K. J., Krull, J. L., & Wood, P. K. (2009). Blue-Collar Scholars?: Mediators and Moderators of University Attrition in First-Generation College Students. *Journal of College Student Development*, *50*(1), 87–103. https://doi.org/10.1353/csd.0.0053

McBride, B. A., Dyer, W. J., Liu, Y., Brown, G. L., & Hong, S. (2009). The Differential Impact of Early Father and Mother Involvement on Later Student Achievement. *Journal of Educational Psychology*, *101*(2), 498–508. https://doi.org/10.1037/a0014238

McCarron, G. P., & Inkelas, K. K. (2006). The Gap between Educational Aspirations and Attainment for First-Generation College Students and the Role of Parental Involvement. *Journal of College Student Development*, *47*(5), 534–549. https://doi.org/10.1353/csd.2006.0059

Møllegaard, S., & Jæger, M. M. (2015). The effect of grandparents' economic, cultural, and social capital on grandchildren's educational success. *Research in Social Stratification and Mobility*, *42*, 11–19. https://doi.org/10.1016/j.rssm.2015.06.004

Moore, G. W., Slate, J. R., Edmonson, S. L., Combs, J. P., Bustamante, R., & Onwuegbuzie, A. J. (2010). High School Students and Their Lack of Preparedness for College: A Statewide Study. *Education and Urban Society*, *42*(7), 817–838. https://doi.org/10.1177/0013124510379619

Moschetti, R. V., & Hudley, C. (2015). Social Capital and Academic Motivation Among First-Generation Community College Students. *Community College Journal of Research and Practice*, *39*(3), 235–251. https://doi.org/10.1080/10668926.2013.819304

Nord, C. W., Brimhall, D., & West, J. (1997). *Fathers' Involvement in Their Children's Schools* (U.S. Department of Education, p. 182). National Center for Education Statistics.

Nunez, A.-M., & Cuccaro-Alamin, S. (1998). First-Generation Students: Undergraduates Whose Parents Never Enrolled in Postsecondary Education. *National Center for Education Statistics*, 100.

Orbe, M. P. (2004). Negotiating multiple identities within multiple frames: An analysis of first-generation college students. *Communication Education*, *53*(2), 131–149. https://doi.org/10.1080/03634520410001682401

Padgett, R. D., Johnson, M. P., & Pascarella, E. T. (2012). First-Generation Undergraduate Students and the Impacts of the First Year of College: Additional Evidence. *Journal of College Student Development*, *53*(2), 243–266. https://doi.org/10.1353/csd.2012.0032

Page, L. C., & Scott-Clayton, J. (2016). Improving college access in the United States: Barriers and policy responses. *Economics of Education Review*, *51*, 4–22. https://doi.org/10.1016/j.econedurev.2016.02.009

Palbusa, J. A., & Gauvain, M. (2017). Parent–Student Communication About College and Freshman Grades in First-Generation and Non–First-Generation Students. *Journal of College Student Development*, *58*(1), 107–112. https://doi.org/10.1353/csd.2017.0007

Pascarella, E. T., Pierson, C. T., Wolniak, G. C., & Terenzini, P. T. (2004). First-Generation College Students: Additional Evidence on College Experiences and Outcomes. *The Journal of Higher Education*, *75*(3), 249–284. JSTOR.

Peralta, K. J., & Klonowski, M. (2017). Examining Conceptual and Operational Definitions of "First-Generation College Student" in Research on Retention. *Journal of College Student Development*, *58*(4), 630–636. https://doi.org/10.1353/csd.2017.0048

Perna, L. W. (2006). Studying College Access and Choice: A Proposed Conceptual Model. In J. C. Smart (Ed.), *Higher Education: Handbook of Theory and Research* (Vol. 21, pp. 99–157). Springer. https://doi.org/10.1007/1-4020-4512-3_3

Pruett, K. (2001). *Fatherneed: Why Father Care is as Essential as Mother Care for Your Child*. Harmony.

Redford, J., Hoyer, K. M., & Ralph, J. (2017). First-Generation and Continuing-Generation College Students: A Comparison of High School and Postsecondary Experiences. *National Center for Education Statistics*, 1–27.

Reid, M. J., & Moore, J. L. (2008). College Readiness and Academic Preparation for Postsecondary Education: Oral Histories of First-Generation Urban College Students. *Urban Education*, *43*(2), 240–261. https://doi.org/10.1177/0042085907312346

Schwartz, S. E. O., Kanchewa, S. S., Rhodes, J. E., Gowdy, G., Stark, A. M., Horn, J. P., Parnes, M., & Spencer, R. (2017). "I'm Having a Little Struggle With This, Can You Help Me Out?": Examining Impacts and Processes of a Social Capital Intervention for First-Generation College Students. *American Journal of Community Psychology*, n/a-n/a. https://doi.org/10.1002/ajcp.12206

Stephens, N. M., Fryberg, S. A., Markus, H. R., Johnson, C. S., & Covarrubias, R. (2012). Unseen disadvantage: How American universities' focus on independence undermines the academic performance of first-generation college students. *Journal of Personality and Social Psychology: Interpersonal Relations and Group Processes*, *102*(6), 1178–1197. http://dx.doi.org/10.1037/a0027143

Tennessee Department of Education. (2019, November 4). *Tennessee ACT Participation at All Time High*. Tennessee Department of Education. https://www.tn.gov/education/news/2019/11/4/tennessee-act-participation-at-all-time-high.html

Tennessee Higher Education Commission. (2019). *Articulation and Transfer in Tennessee Higher Education* (pp. 1–25).

Terenzini, P. T., Springer, L., Yaeger, P. M., Pascarella, E. T., & Nora, A. (1996). First-generation college students: Characteristics, experiences, and cognitive development. *Research in Higher Education*, *37*(1), 1–22.

Tinto, V. (1993). *Leaving College: Rethinking the Causes and Cures of Student Attrition* (2nd edition). University of Chicago Press.

Tobolowsky, B. F., Cox, B. E., & Chunoo, V. S. (2017). Bridging the Cultural Gap: Relationships Between Programmatic Offerings and First-Generation Student

Benchmarks. *Journal of College Student Retention: Research, Theory & Practice*, *0*(0), 1–25. https://doi.org/10.1177/1521025117742377

Toutkoushian, R. K., May-Trifiletti, J. A., & Clayton, A. B. (2019). From “First in Family” to “First to Finish”: Does College Graduation Vary by How First-Generation College Status Is Defined? *Educational Policy*, 089590481882375. https://doi.org/10.1177/0895904818823753

Toutkoushian, R. K., Stollberg, R. A., & Slaton, K. A. (2018). Talking ’Bout My Generation: Defining “First-Generation College Students” in Higher Education Research. *Teachers College Record*, 38.

Higher Education Act of 1965, 1998 Higher Education Act Amendments, Subpart 2—Federal Early Outreach and Student Services Programs, 402A. 20 U.S.C. 1070a-11 Chapter 1—Federal Trio Programs (1998). https://www2.ed.gov/policy/highered/leg/hea98/sec402.html

U.S. Department of Labor. (2018). *Labor Force Participation Rate by Sex and State*. Women’s Bureau. https://www.dol.gov/wb/stats/LaborForceParticipationRatebySex-text.htm

Vaughan, A., Parra, J., & Lalonde, T. (2014). First-Generation College Student Achievement and the First-Year Seminar: A Quasi-Experimental Design. *Journal of The First-Year Experience & Students in Transition*, *26*(2), 51–67.

Warburton, E. C., Bugarin, R., & Nuñez, A.-M. (2001). *Bridging the Gap: Academic Preparation and Postsecondary Success of First-Generation Students* (NCES 2001-153; Postsecondary Education Descriptive Analysis Reports, p. 83). U.S. Department of Education Office of Educational Research and Improvement.

Ward, L., Siegel, M. J., & Davenport, Z. (2012). *First-generation college students: Understanding and improving the experience from recruitment to commencement*. John Wiley & Sons. http://books.google.com/books?hl=en&lr=&id=g6D0pD3KBsMC&oi=fnd&pg=PT17&dq=%22make+further+tacit+assumptions+about+ethnic%22+%22in+your+ability+to+intuit+demographic%22+%22you+identify+the+students+who+represent+the+%EF%AC%81rst+in%22+%22be+nothing+compelling+them+to+do+so%E2%80%94they+tend+to%22+&ots=ajA27KxvXl&sig=tbY6BOH7EAzvqIY1h3dEojybVDY

Whitley, S. E., Benson, G., & Wesaw, A. (2018). First-generation student success: A landscape of analysis of programs and services at four-year institutions. *NASPA—Student Affairs Administrators in Higher Education*, 84.

Wilbur, T. G., & Roscigno, V. J. (2016). First-generation Disadvantage and College Enrollment/Completion. *Socius*, *2*, 2378023116664351. https://doi.org/10.1177/2378023116664351

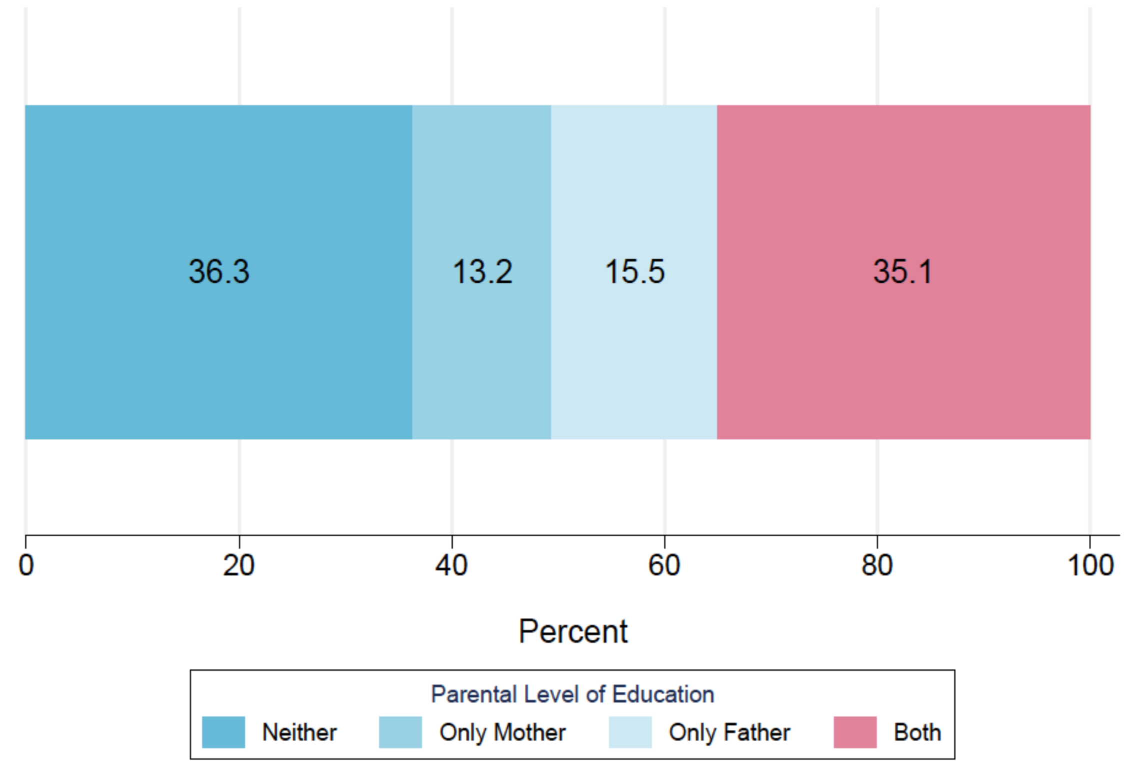
Wildhagen, T. (2015). "Not Your Typical Student": The Social Construction of the "First-Generation" College Student. *Qualitative Sociology*, *38*(3), 285–303. https://doi.org/10.1007/s11133-015-9308-1

Willis, P. (1981). *Learning to Labor: How Working Class Kids Get Working Class Jobs* (Morningside edition). Columbia University Press.

Wooldridge, J. M. (2012). *Introductory Econometrics: A Modern Approach* (5th Edition). Cengage Learning.

Tables and Figures

Figure 2- 1 Percent First-Time First-Year Students in Tennessee, by Parental Education



Note: Figures shows the percent of students in the analytic sample by parental education (N=189,358). "Neither" indicates student had no degree-holding parents. "Only mother" or "only father" indicates only one parent held a degree, while the other parent did not. "Both" indicates student had two degree-holding parents. Data on parental education obtained from FAFSA forms filled for the 2010/11 - 2017/18 school years.

Table 2- 1 Descriptive Statistics of Predictors, by First-Generation Status

	First-Generation Status			Overall Characteristics		
	Neither College	One Parent College	Both College	Sample Average	Min	Max
Demographic Characteristics						
Male	40.74%	45.07%	47.87%	44.48%	0%	100%
Female	59.26%	54.93%	52.13%	55.52%	0%	100%
White	65.32%	69.04%	73.08%	69.11%	0%	100%
Black	20.69%	20.35%	16.73%	19.20%	0%	100%
Latinx	5.70%	2.91%	2.40%	3.74%	0%	100%
Asian	2.32%	1.36%	1.86%	1.88%	0%	100%
Other	5.97%	6.34%	5.93%	6.06%	0%	100%
Academic Preparedness						
ACT Composite	19.67	20.48	21.85	20.67	1	36
ACT Composite (Bottom 25%)	39.98%	32.03%	21.83%	31.34%	0%	100%
ACT Composite (25-50%]	30.02%	30.12%	27.12%	29.03%	0%	100%
ACT Composite (50-75%]	19.16%	22.56%	25.49%	22.35%	0%	100%
ACT Composite (Top 25%)	10.83%	15.30%	25.56%	17.28%	0%	100%
Never Dual Enrolled in H.S.	92.18%	89.81%	83.07%	88.31%	0%	100%
Dual Enrolled in H.S.	7.82%	10.19%	16.93%	11.69%	0%	100%
First Enrolled at Age 17	0.82%	0.53%	1.47%	0.86%	0%	100%
First Enrolled at Age 18	44.28%	45.83%	45.17%	45.04%	0%	100%
First Enrolled at Age 19-24	54.90%	53.31%	53.93%	54.11%	0%	100%
Financial Resources						
Student Adjusted Gross Income	$2,008	$1,977	$2,477	$2,163	$1	$8,500,000+
Parent Adjusted Gross Income	$44,003	$66,164	$102,645	$70,915	$1	$8,100,000+
Parental EFC	$6,655	$13,968	$29,416	$16,731	$1	$3,700,000+
Parental EFC < $6,000	71.19%	52.28%	34.24%	52.82%	0%	100%

Parental EFC $6,000-21,000	20.91%	27.96%	26.91%	25.03%	0%	100%
Parental EFC $21,000-75,000	7.11%	17.13%	29.60%	17.87%	0%	100%
Parental EFC $75,000 +	0.79%	2.63%	9.24%	4.28%	0%	100%
Pell Eligible	70.71%	52.54%	35.06%	53.00%	0%	100%
TSAA Eligible	40.25%	27.91%	15.50%	28.04%	0%	100%
HOPE Access Eligible	1.55%	1.11%	0.65%	1.11%	0%	100%
HOPE Aspire Eligible	30.23%	19.90%	13.25%	21.32%	0%	100%
HOPE GAM Eligible	0.81%	1.86%	4.86%	2.53%	0%	100%
HOPE Eligible	32.41%	46.44%	58.96%	45.74%	0%	100%
Institutional						
Community College	55.55%	49.17%	35.85%	46.82%	0%	100%
Four-Year College	44.45%	50.83%	64.15%	53.18%	0%	100%
Unknown/General Major	49.56%	49.73%	47.56%	48.91%	0%	100%
Arts/Humanities Major	6.72%	6.74%	6.74%	6.73%	0%	100%
Business Major	6.44%	6.75%	8.15%	7.13%	0%	100%
Health/Medicine Major	18.03%	15.06%	12.62%	15.28%	0%	100%
STEM Major	9.40%	11.38%	14.50%	11.76%	0%	100%
Social Sciences Major	6.97%	7.42%	8.14%	7.51%	0%	100%
Trade Major	2.88%	2.91%	2.29%	2.68%	0%	100%
Seamless Enrollment	86.54%	89.18%	90.87%	88.81%	0%	100%
Full Time Enrollment	94.11%	95.11%	95.99%	95.06%	0%	100%
N Observations	68,717	54,239	66,402	189,358		

Note: Table shows difference in characteristics between first-generation and non-first-generation students in their first term of enrollment across all predictors in the analytic sample. Column 1 shows mean values for students with no degree-holding parents. Column 2 shows means for students with one degree-holding parent. Column 3 shows means for students for with two degree-holding parents. Column 4 shows the mean value for the analytic sample. Columns 5 and 6 show the minimum and maximum values of the variable in the sample. H.S. is high school.

Table 2- 2 Descriptive Statistics of Outcomes, by First-Generation Status

	First-Generation Status			Overall Characteristics		
	Neither College	One Parent College	Both College	Sample Average	Min	Max
First Term Credits						
Credits Attempted	13.57	13.80	14.07	13.81	1	22
Credits Earned	11.19	11.56	12.22	11.66	0	22
Percent Credits Earned	82.30%	83.43%	86.64%	84.15%	0%	100%
GPA	2.51	2.56	2.73	2.60	0	4
Cumulative Credits						
Credits Attempted	15.60	16.23	16.87	16.22	1	42
Credits Earned	12.94	13.67	14.65	13.75	1	39
Percent Credits Earned	82.45%	83.54%	86.31%	84.11%	3%	100%
GPA	2.54	2.59	2.75	2.63	0	4
N Observations	68,717	54,239	66,402	189,358		

Note: Table shows difference in characteristics between first-generation and non-first-generation students in their first term of enrollment across all outcomes in the analytic sample. Column 1 shows mean values for students for with no degree-holding parents. Column 2 shows means for students with one degree-holding parent. Column 3 shows means for students with two degree-holding parents. Column 4 shows the mean value for the analytic sample. Columns 5 and 6 show the minimum and maximum values of the variable in the sample.

Table 2- 3 Estimates of First-Term Academic Outcomes by First-Generation Status (Binary Measure)

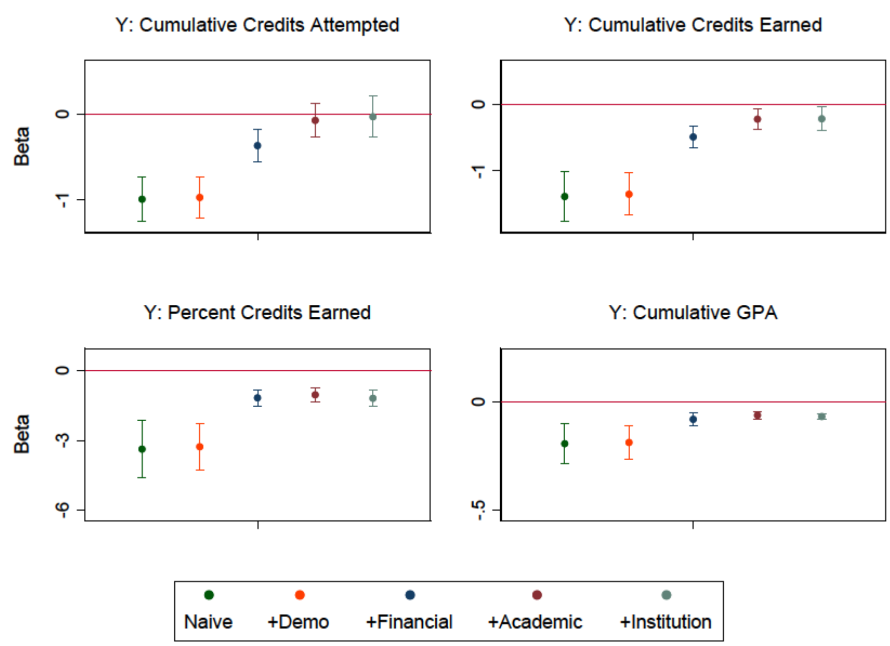
	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
At Least One Parent No Degree	-0.052***	-0.220***	-0.070***	-1.255***	-0.032	-0.218*	-0.066***	-1.182***
	(0.008)	(0.023)	(0.007)	(0.160)	(0.116)	(0.086)	(0.006)	(0.166)
Constant	7.357***	5.978***	2.244***	81.102***	6.555***	4.418**	2.260***	78.236***
	(0.137)	(0.287)	(0.095)	(2.119)	(1.422)	(1.159)	(0.085)	(1.840)
Adj. R2	0.523	0.243	0.140	0.093	0.248	0.253	0.148	0.093
N	189,358	189,358	189,358	189,358	189,358	189,358	189,358	189,358

Note: Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Binary indicator of first-generation equals one for students who have no or one degree-holding parent. The reference category is non-first-generation students, i.e. students with two degree-holding parents. Standard errors are clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Figure 2- 2 Variation in Estimates with the Inclusion of Covariates

Panel A: Term Credits

Panel B: Panel Cumulative Credits



Note: Figures show the change in the naïve differences (leftmost point estimate in green) between first-generation and non-first-generation students with the addition of study covariates. Panel A displays term-level outcomes in students' first term and Panel B shows cumulative outcomes by the end of students' first term.

Table 2- 4 Estimates of First-Term Academic Outcomes by First-Generation Status (Categorical Measures)

	Panel A: Three-Category Measure of First-Generation Status							
	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
Neither Parent Has Degree	-0.064***	-0.242***	-0.072***	-1.322***	-0.094	-0.286**	-0.069***	-1.261***
	(0.010)	(0.027)	(0.007)	(0.168)	(0.112)	(0.081)	(0.006)	(0.176)
One Parent No Degree	-0.040***	-0.197***	-0.068***	-1.188***	0.030	-0.150	-0.062***	-1.102***
	(0.008)	(0.028)	(0.008)	(0.190)	(0.116)	(0.089)	(0.007)	(0.187)
Constant	7.362***	5.986***	2.245***	81.128***	6.579***	4.444***	2.261***	78.267***
	(0.137)	(0.285)	(0.094)	(2.102)	(1.422)	(1.159)	(0.085)	(1.825)
Wald Test								
Pr(Neither Parent College = One Parent)	**0.017**	0.110	0.512	0.415	**0.000**	**0.000**	0.247	0.260
Adj. R2	0.523	0.243	0.140	0.093	0.248	0.253	0.148	0.093
N	189,358	189,358	189,358	189,358	189,358	189,358	189,358	189,358

	Panel B: Four-Category Measure of First-Generation Status							
	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
Neither Parent Has Degree	-0.064***	-0.242***	-0.072***	-1.321***	-0.095	-0.286**	-0.069***	-1.260***
	(0.010)	(0.027)	(0.007)	(0.169)	(0.113)	(0.081)	(0.006)	(0.177)
Only Mother Has Degree	-0.052***	-0.232***	-0.073***	-1.402***	0.168	-0.054	-0.065***	-1.348***
	(0.007)	(0.027)	(0.008)	(0.185)	(0.134)	(0.099)	(0.007)	(0.192)
Only Father Has Degree	-0.030*	-0.167***	-0.063***	-1.001***	-0.091	-0.233*	-0.059***	-0.887**
	(0.013)	(0.039)	(0.011)	(0.247)	(0.107)	(0.090)	(0.010)	(0.234)
Constant	7.363***	5.990***	2.246***	81.148***	6.567***	4.435***	2.262***	78.290***
	(0.137)	(0.285)	(0.094)	(2.101)	(1.421)	(1.159)	(0.085)	(1.823)
Wald Tests								
Pr(Neither College = Mother Only)	0.221	0.739	0.962	0.637	**0.000**	**0.000**	0.605	0.560
Pr(Neither College = Father Only)	**0.018**	**0.047**	0.310	0.151	0.909	0.206	0.221	0.068
Pr(Mother Only = Father Only)	0.143	0.107	0.309	0.087	**0.000**	**0.007**	0.544	**0.043**
Adj. R2	0.523	0.243	0.140	0.093	0.248	0.253	0.148	0.093
N	189,358	189,358	189,358	189,358	189,358	189,358	189,358	189,358

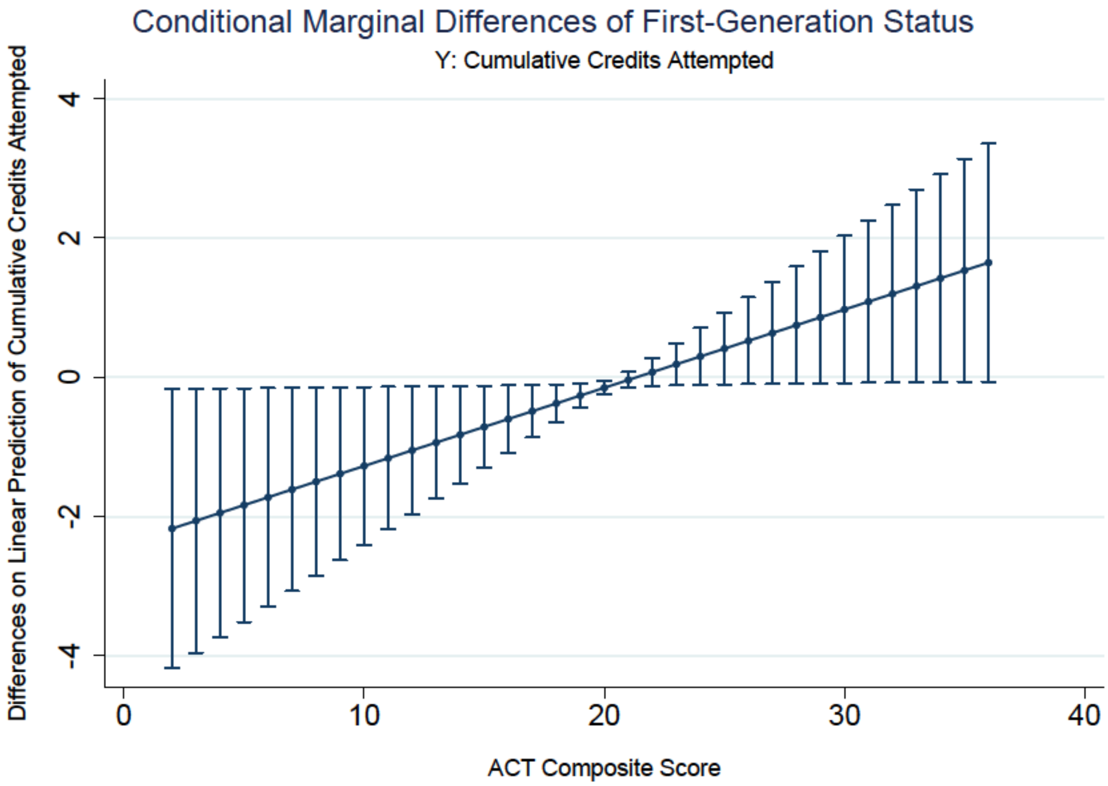
Note: Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Panel A shows results using a categorical variable of first-generation status with two different categories of first-generation students (no degree-holding parents and one degree-holding parent), and Panel B shows results using a categorical variable with three categories of first-generation (no degree-holding parents, or, only mother or only father is degree-holding). The reference category is non-first-generation students, i.e. those with two degree-holding parents. Tests of regression coefficient equivalence (Wald Tests) show whether differences between estimated coefficients between each category of first-generation student are statistically significant (bolded). Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Table 2- 5 Interaction Models: Continuous Measure of ACT Composite Score

	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
First-Generation	-0.049	-0.288*	-0.059	-2.426*	-2.399*	-2.276*	-0.073*	-1.934
	(0.063)	(0.118)	(0.031)	(0.911)	(1.069)	(0.856)	(0.026)	(0.987)
ACT Composite	0.066***	0.042**	0.018***	-0.117	0.113	0.107	0.021***	0.074
	(0.006)	(0.014)	(0.004)	(0.103)	(0.100)	(0.079)	(0.004)	(0.076)
First-Generation * ACT	-0.000	0.003	-0.001	0.056	0.112*	0.098*	0.000	0.036
	(0.003)	(0.006)	(0.002)	(0.047)	(0.052)	(0.041)	(0.001)	(0.051)
Constant	7.354***	6.025***	2.237***	81.905***	8.178***	5.829**	2.265***	78.752***
	(0.144)	(0.315)	(0.099)	(2.415)	(2.060)	(1.610)	(0.089)	(2.154)
Adj. R2	0.523	0.243	0.140	0.093	0.250	0.254	0.148	0.093
N	189,358	189,358	189,358	189,358	189,358	189,358	189,358	189,358

Note: Models include an interaction term between the continuous, logged measure of students' ACT composite score and the binary indicator of first-generation status. Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Binary indicator of first-generation equals one for students who have no degree-holding parents or only one degree-holding parent. The reference category is non-first-generation students, i.e. students with two degree-holding parents. Standard errors clustered by institution and are in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Figure 2- 3 Conditional Marginal Differences of First-Generation Status on Cumulative Credits Attempted, by ACT Composite Score



Note: Figure visually displays the interaction term between first-generation students and composite ACT score in the model predicting cumulative credits attempted, as shown in Table 2-5. Figure shows the change in the marginal difference for first-generation students' cumulative credits attempted from a linear change in ACT composite score. Each point shows the marginal difference between first-generation and non-first-generation students at each ACT score.

Table 2- 6 Interaction Models: Categorical Measure of ACT Composite Score

	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
First-Generation	-0.077***	-0.269***	-0.078***	-1.498***	-0.299**	-0.469***	-0.072***	-1.330***
	(0.011)	(0.030)	(0.010)	(0.200)	(0.091)	(0.100)	(0.009)	(0.167)
ACT Composite Score: 1-18	-0.318***	-0.156**	0.014	0.811*	-1.079***	-0.831***	-0.004	0.473
	(0.040)	(0.043)	(0.019)	(0.372)	(0.166)	(0.146)	(0.019)	(0.329)
ACT Composite Score: 22-24	0.151***	-0.000	0.041*	-1.122*	0.669*	0.581*	0.048**	-0.602
	(0.028)	(0.076)	(0.017)	(0.486)	(0.256)	(0.222)	(0.016)	(0.460)
ACT Composite Score: 25-36	0.350***	0.193	0.161***	-1.087	0.448	0.508	0.171***	0.353
	(0.040)	(0.133)	(0.029)	(0.887)	(0.752)	(0.610)	(0.027)	(0.585)
First-Generation * ACT 1-18	0.034	0.044	0.002	0.020	0.029	0.043	-0.005	-0.074
	(0.020)	(0.052)	(0.012)	(0.327)	(0.090)	(0.095)	(0.012)	(0.306)
First-Generation * ACT 22-24	0.031	0.104*	0.019	0.655*	0.226	0.220	0.018	0.375
	(0.016)	(0.045)	(0.013)	(0.314)	(0.176)	(0.148)	(0.011)	(0.267)
First-Generation * ACT 25-36	0.018	0.032	0.006	0.281	1.063**	0.957**	0.005	0.217
	(0.016)	(0.033)	(0.013)	(0.258)	(0.374)	(0.294)	(0.011)	(0.332)
Constant	8.700***	6.870***	2.536***	79.532***	10.580***	8.013***	2.623***	79.896***
	(0.096)	(0.175)	(0.056)	(1.379)	(0.399)	(0.383)	(0.052)	(1.314)
Adj. R2	0.522	0.243	0.139	0.094	0.253	0.255	0.147	0.093
N	189,358	189,358	189,358	189,358	189,358	189,358	189,358	189,358

Note: Models include interaction terms between a categorical measures of students' ACT composite and the binary indicator of first-generation status. The omitted category is an ACT composite between 19-21, i.e. the second quartile from the bottom containing the minimum scores for college readiness. Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Binary indicator of first-generation equals one for students who have no degree-holding parents or only one degree-holding parent. The reference category is non-first-generation students, i.e. those with two degree-holding parents. Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Table 2- 7 Interaction Models: Continuous Measure of Parental Income

	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
First-Generation	-0.046**	-0.244***	-0.076***	-1.565***	-0.152***	-0.332***	-0.072***	-1.389***
	(0.015)	(0.039)	(0.007)	(0.236)	(0.039)	(0.053)	(0.008)	(0.226)
Parents' Income (ln)	0.005	0.011	0.001	0.032	-0.034	-0.017	0.000	0.038
	(0.004)	(0.008)	(0.002)	(0.049)	(0.026)	(0.023)	(0.002)	(0.042)
First-Generation * Income (ln)	-0.002	0.007	0.002	0.091*	0.035	0.034	0.002	0.061
	(0.004)	(0.007)	(0.002)	(0.041)	(0.032)	(0.027)	(0.002)	(0.036)
Constant	7.351***	6.000***	2.250***	81.384***	6.664***	4.521**	2.265***	78.424***
	(0.136)	(0.286)	(0.094)	(2.124)	(1.501)	(1.219)	(0.085)	(1.852)
Adj. R2	0.523	0.243	0.140	0.093	0.248	0.253	0.148	0.093
N	189,358	189,358	189,358	189,358	189,358	189,358	189,358	189,358

Note: Models include an interaction term between the continuous, logged measure of parental adjusted gross income (AGI) and the binary indicator of first-generation status. Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Binary indicator of first-generation equals one for students who have no degree-holding parents or only one degree-holding parent. The reference category is non-first-generation students, i.e. those with two degree-holding parents. Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Table 2- 8 Interaction Models: Categorical Measure of Parental Income

	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
First-Generation	-0.059***	-0.240***	-0.071***	-1.359***	-0.182	-0.366***	-0.066***	-1.338***
	(0.012)	(0.032)	(0.009)	(0.209)	(0.093)	(0.078)	(0.009)	(0.183)
Parental Income: ($1-60,000]	-0.052**	-0.145**	-0.019	-0.701*	-0.175**	-0.256**	-0.017	-0.649
	(0.015)	(0.044)	(0.013)	(0.321)	(0.054)	(0.071)	(0.012)	(0.329)
Parental Income: ($100,000-200,000]	0.055	0.104*	0.028**	0.236	-0.125	-0.037	0.026**	0.135
	(0.027)	(0.038)	(0.010)	(0.234)	(0.133)	(0.114)	(0.008)	(0.230)
Parental Income: ($200,000 +]	-0.047	-0.082	0.008	-0.430	-1.162**	-1.005***	0.005	-0.208
	(0.063)	(0.047)	(0.012)	(0.329)	(0.338)	(0.240)	(0.011)	(0.467)
First-Generation* Income ($1-60,000]	0.021	0.050	0.013	0.178	0.094	0.128	0.009	0.246
	(0.016)	(0.040)	(0.011)	(0.279)	(0.065)	(0.069)	(0.010)	(0.288)
First-Generation* Income ($100,000-200,000]	-0.008	0.017	-0.011	0.189	0.200*	0.202*	-0.007	0.343
	(0.024)	(0.038)	(0.013)	(0.288)	(0.072)	(0.075)	(0.012)	(0.270)
First-Generation * Income ($200,000 +]	-0.002	-0.073	-0.033	-0.533	0.779**	0.560**	-0.038*	-0.622
	(0.047)	(0.078)	(0.018)	(0.566)	(0.206)	(0.186)	(0.016)	(0.473)
Constant	7.367***	6.035***	2.245***	81.546***	6.726***	4.612***	2.260***	78.629***
	(0.138)	(0.283)	(0.095)	(2.126)	(1.495)	(1.201)	(0.086)	(1.896)
Adj. R2	0.523	0.244	0.140	0.093	0.249	0.254	0.148	0.093
N	189,358	189,358	189,358	189,358	189,358	189,358	189,358	189,358

Note: Models include interaction terms between a categorical measure of parental adjusted gross income (AGI) and the binary indicator of first-generation status. The omitted category is a parental income between $60,000 and $100,000, i.e. the second quartile from the bottom containing the mean income in the sample. Values rounded for confidentiality. Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Binary indicator of first-generation equals one for students who have no degree-holding parents or only one degree-holding parent. The reference category is non-first-generation students, i.e. those with two degree-holding parents. Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Table 2- 9 Interaction Models: Continuous Measure of Expected Financial Contribution

	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
First-Generation	-0.045***	-0.220***	-0.067***	-1.331***	-0.091	-0.265***	-0.063***	-1.213***
	(0.010)	(0.029)	(0.007)	(0.191)	(0.064)	(0.053)	(0.007)	(0.190)
Parents' EFC (ln)	0.008*	0.042***	0.012***	0.277***	-0.028	0.015	0.012***	0.281***
	(0.003)	(0.008)	(0.003)	(0.067)	(0.019)	(0.015)	(0.002)	(0.063)
First-Generation * Parent EFC (ln)	-0.003	0.000	-0.001	0.032	0.025	0.020	-0.001	0.013
	(0.003)	(0.005)	(0.001)	(0.032)	(0.023)	(0.018)	(0.001)	(0.033)
Constant	7.349***	5.978***	2.241***	81.190***	6.624***	4.472**	2.257***	78.273***
	(0.137)	(0.287)	(0.095)	(2.131)	(1.478)	(1.197)	(0.086)	(1.853)
Adj. R2	0.523	0.243	0.140	0.093	0.248	0.253	0.148	0.093
N	189,358	189,358	189,358	189,358	189,358	189,358	189,358	189,358

Note: Models include an interaction term between the continuous, logged measure of parental expected financial contribution (EFC) and the binary indicator of first-generation status. Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Binary indicator of first-generation equals one for students who have no degree-holding parents or only one degree-holding parent. The reference category is non-first-generation students, i.e. those with two degree-holding parents. Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Table 2- 10 Interaction Models: Categorical Measure of Expected Financial Contribution

	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
First-Generation	-0.065***	-0.212***	-0.066***	-1.158***	-0.183*	-0.342***	-0.061***	-1.185***
	-0.013	-0.026	-0.01	-0.171	-0.086	-0.059	-0.009	-0.161
Parental EFC: ($1-6,000]	-0.089***	-0.225***	-0.045**	-1.110*	-0.195**	-0.351***	-0.042**	-1.217**
	-0.016	-0.058	-0.016	-0.392	-0.061	-0.087	-0.014	-0.38
Parental EFC: ($21,000-75,000]	0.046	0.141***	0.038**	0.551**	-0.145	0.003	0.037**	0.476**
	-0.025	-0.03	-0.011	-0.176	-0.158	-0.136	-0.01	-0.168
Parental EFC: ($75,000 +]	-0.048	0.061	0.057***	0.568*	-1.099**	-0.821**	0.054***	0.632
	-0.066	-0.06	-0.01	-0.256	-0.348	-0.269	-0.01	-0.331
First-Generation * EFC ($1-6,000]	0.027	-0.006	0	-0.232	0.072	0.059	-0.003	-0.088
	-0.019	-0.033	-0.012	-0.238	-0.064	-0.055	-0.011	-0.251
First-Generation * EFC ($21000-75,000]	0.001	-0.001	-0.007	0.053	0.256*	0.242*	-0.003	0.262
	-0.024	-0.03	-0.012	-0.22	-0.101	-0.097	-0.012	-0.184
First-Generation * EFC ($75,000 +]	0.042	-0.065	-0.019	-0.664	0.946***	0.701***	-0.025	-0.66
	-0.043	-0.092	-0.026	-0.611	-0.157	-0.165	-0.025	-0.49
Constant	7.362***	5.958***	2.233***	81.008***	6.726***	4.537**	2.249***	78.191***
	-0.139	-0.281	-0.093	-2.099	-1.499	-1.215	-0.084	-1.828
Adj. R2	0.523	0.243	0.139	0.093	0.249	0.254	0.148	0.092
N	189,358	189,358	189,358	189,358	189,358	189,358	189,358	189,358

Note: Models include interaction terms between a categorical measure of parental expected financial contribution (EGC) and the binary indicator of first-generation status. The omitted category is a parental EFC between $6,000 and $21,000, i.e. the second quartile from the bottom containing the mean EFC in the sample. Values rounded for confidentiality. Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Binary indicator of first-generation equals one for students who have no degree-holding parents or only one degree-holding parent. The reference category is non-first-generation students, i.e. those with two degree-holding parents. Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Table 2- 11 Correlation Matrix of Measures of Student Enrollment Behaviors

	(1)	(2)	(3)	(4)	(5)
(1) Seamless Enrollment	1				
(2) Full Time Enrollment	0.23	1			
(3) Earned AP Credits in H.S.	0.03	0.02	1		
(4) Dual Enrolled in H.S.	0.03	0.04	0.05	1	
(5) Age at Time of Enrollment	-0.10	-0.05	0.004	-0.02	1

Note: Table shows correlations between each variable included in the heterogeneity analyses. Correlations shown using the analytic sample (N = 189,358). H.S. is high school.

Table 2- 12 Estimates Excluding Students Who Enroll Part Time; Binary Measure of First-Generation Status

	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
At Least One Parent No Degree	-0.061***	-0.224***	-0.067***	-1.183***	-0.026	-0.212*	-0.063***	-1.150***
	(0.009)	(0.024)	(0.007)	(0.176)	(0.122)	(0.090)	(0.006)	(0.180)
Constant	12.447***	9.955***	2.180***	80.254***	11.116***	8.061***	2.152***	77.179***
	(0.137)	(0.269)	(0.092)	(1.904)	(1.476)	(1.218)	(0.083)	(1.544)
Adj. R2	0.232	0.159	0.143	0.095	0.191	0.214	0.150	0.094
N	179,996	179,996	179,996	179,996	179,996	179,996	179,996	179,996

Note: Models exclude students who enroll part time, i.e. take fewer than 12 credits in their first term. Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Binary indicator of first-generation equals one for students who have no degree-holding parents or only one degree-holding parent. The reference category is non-first-generation students, i.e. those with two degree-holding parents. Standard errors clustered by institution and are in parentheses.
* p<0.05 **p<0.01 ***p<0.001.

Table 2- 13 Estimates Excluding Students Who Enroll Part Time; Categorical Measure of First-Generation Status

	Panel A: Three-Category Measure of First-Generation Status							
	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
Neither Parent Has Degree	-0.076***	-0.251***	-0.070***	-1.266***	-0.092	-0.285**	-0.067***	-1.237***
	(0.010)	(0.027)	(0.007)	(0.190)	(0.119)	(0.086)	(0.007)	(0.192)
One Parent No Degree	-0.046***	-0.197***	-0.063***	-1.101***	0.039	-0.139	-0.059***	-1.064***
	(0.009)	(0.029)	(0.009)	(0.205)	(0.122)	(0.093)	(0.008)	(0.202)
Constant	12.453***	9.966***	2.181***	80.287***	11.142***	8.091***	2.154***	77.213***
	(0.137)	(0.268)	(0.091)	(1.891)	(1.476)	(1.219)	(0.083)	(1.531)
Wald Test								
Pr(Neither Parent College = One Parent)	**0.005**	0.074	0.364	0.356	**0.000**	**0.000**	0.208	0.276
Adj. R2	0.232	0.159	0.143	0.095	0.191	0.214	0.150	0.094
N	179,996	179,996	179,996	179,996	179,996	179,996	179,996	179,996

	Panel B: Four-Category Measure of First-Generation Status							
	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
Neither Parent Has Degree	-0.076***	-0.251***	-0.070***	-1.265***	-0.093	-0.285**	-0.067***	-1.235***
	(0.010)	(0.027)	(0.007)	(0.190)	(0.119)	(0.086)	(0.007)	(0.193)
Only Mother Has Degree	-0.058***	-0.232***	-0.068***	-1.310***	0.182	-0.039	-0.063***	-1.307***
	(0.009)	(0.029)	(0.008)	(0.202)	(0.140)	(0.103)	(0.008)	(0.208)
Only Father Has Degree	-0.036*	-0.168***	-0.059***	-0.921**	-0.083	-0.224*	-0.056***	-0.855**
	(0.014)	(0.040)	(0.011)	(0.267)	(0.112)	(0.095)	(0.010)	(0.257)
Constant	12.454***	9.969***	2.182***	80.304***	11.130***	8.083***	2.154***	77.234***
	(0.137)	(0.267)	(0.091)	(1.890)	(1.475)	(1.219)	(0.083)	(1.530)
Wald Tests								
Pr(Neither College = Mother Only)	0.081	0.569	0.855	0.823	**0.000**	**0.000**	0.559	0.691
Pr(Neither College = Father Only)	**0.008**	**0.034**	0.230	0.142	0.790	0.153	0.189	0.085
Pr(Mother Only = Father Only)	0.138	0.123	0.355	0.131	**0.000**	**0.007**	0.565	0.075
Adj. R2	0.232	0.159	0.143	0.095	0.191	0.214	0.150	0.094
N	179,996	179,996	179,996	179,996	179,996	179,996	179,996	179,996

Note: Models exclude students who enroll part time, i.e. take fewer than 12 credits in their first term. Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Panel A shows results using a categorical variable of first-generation status with two different categories of first-generation students (no degree-holding parents and one degree-holding parent), and Panel B shows results using a categorical variable with three categories of first-generation (no degree-holding parents, or, only mother or only father is degree-holding). The reference category is non-first-generation students, i.e. those with two degree-holding parents. Tests of regression coefficient equivalence (Wald Tests) show whether differences between estimated coefficients between each category of first-generation student are statistically significant (bolded). Standard errors clustered by institution and are in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Table 2- 14 Estimates Excluding Students who do not Seamlessly Enroll; Binary Measure of First-Generation Status

	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
At Least One Parent No Degree	-0.058***	-0.233***	-0.071***	-1.299***	-0.005	-0.207*	-0.068***	-1.249***
	(0.009)	(0.025)	(0.007)	(0.164)	(0.120)	(0.088)	(0.006)	(0.175)
Constant	7.767***	6.004***	2.140***	78.230***	5.485***	3.459**	2.095***	75.797***
	(0.123)	(0.316)	(0.108)	(2.441)	(1.384)	(1.132)	(0.096)	(2.120)
Adj. R2	0.441	0.217	0.150	0.099	0.254	0.251	0.158	0.097
N	168,178	168,178	168,178	168,178	168,178	168,178	168,178	168,178

Note: Models exclude students who do not seamlessly enroll in college in the fall immediately following high school graduation. Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Binary indicator of first-generation equals one for students who have no degree-holding parents or only one degree-holding parent. The reference category is non-first-generation students, i.e. those with two degree-holding parents. Standard errors clustered by institution and are in parentheses.
* p<0.05 **p<0.01 ***p<0.001.

Table 2- 15 Estimates Excluding Students who do not Seamlessly Enroll; Categorical Measure of First-Generation Status

	Panel A: Three-Category Measure of First-Generation Status							
	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
Neither Parent Has Degree	-0.075***	-0.268***	-0.077***	-1.434***	-0.082	-0.298**	-0.075***	-1.392***
	(0.011)	(0.030)	(0.007)	(0.187)	(0.119)	(0.084)	(0.007)	(0.190)
One Parent No Degree	-0.042***	-0.198***	-0.065***	-1.167***	0.071	-0.118	-0.061***	-1.109***
	(0.010)	(0.028)	(0.008)	(0.187)	(0.118)	(0.089)	(0.007)	(0.194)
Constant	7.774***	6.018***	2.143***	78.283***	5.515***	3.494**	2.098***	75.853***
	(0.124)	(0.314)	(0.107)	(2.425)	(1.383)	(1.133)	(0.096)	(2.108)
Wald Test								
Pr(Neither Parent College = One Parent)	**0.002**	**0.026**	0.092	0.133	**0.000**	**0.000**	**0.037**	0.064
Adj. R2	0.441	0.217	0.150	0.099	0.254	0.251	0.158	0.097
N	168,178	168,178	168,178	168,178	168,178	168,178	168,178	168,178

	Panel B: Four-Category Measure of First-Generation Status							
	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
Neither Parent Has Degree	-0.075***	-0.268***	-0.077***	-1.432***	-0.083	-0.299**	-0.075***	-1.390***
	(0.011)	(0.030)	(0.007)	(0.187)	(0.119)	(0.085)	(0.007)	(0.190)
Only Mother Has Degree	-0.055***	-0.230***	-0.069***	-1.346***	0.219	-0.009	-0.062***	-1.328***
	(0.010)	(0.030)	(0.008)	(0.198)	(0.135)	(0.098)	(0.009)	(0.215)
Only Father Has Degree	-0.030*	-0.171***	-0.062***	-1.012***	-0.055	-0.211*	-0.060***	-0.922**
	(0.014)	(0.039)	(0.010)	(0.253)	(0.108)	(0.094)	(0.010)	(0.248)
Constant	7.775***	6.020***	2.143***	78.298***	5.503***	3.486**	2.098***	75.871***
	(0.124)	(0.314)	(0.107)	(2.425)	(1.383)	(1.133)	(0.096)	(2.107)
Wald Tests								
Pr(Neither College = Mother Only)	0.092	0.299	0.361	0.682	**0.000**	**0.000**	0.198	0.735
Pr(Neither College = Father Only)	**0.003**	**0.016**	0.081	0.076	0.428	0.051	0.064	**0.032**
Pr(Mother Only = Father Only)	0.129	0.179	0.543	0.225	**0.000**	**0.006**	0.827	0.133
Adj. R2	0.441	0.217	0.150	0.099	0.254	0.251	0.158	0.097
N	168,178	168,178	168,178	168,178	168,178	168,178	168,178	168,178

Note: Models exclude students who do not seamlessly enroll in college in the fall immediately following high school graduation. Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Panel A shows results using a categorical variable of first-generation status with two different categories of first-generation students (no degree-holding parents and one degree-holding parent), and Panel B shows results using a categorical variable with three categories of first-generation (no degree-holding parents, or, only mother or only father is degree-holding). The reference category is non-first-generation students, i.e. those with two degree-holding parents Tests of regression coefficient equivalence (Wald Tests) show whether differences between estimated coefficients between each category of first-generation student are statistically significant (bolded). Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Table 2- 16 Estimates Excluding Students who are Below or Above Traditional Age; Binary Measure of First-Generation Status

	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
At Least One Parent No Degree	-0.063***	-0.225***	-0.070***	-1.214***	-0.058	-0.243*	-0.067***	-1.202***
	(0.008)	(0.031)	(0.007)	(0.212)	(0.120)	(0.091)	(0.007)	(0.208)
Constant	7.329***	5.578***	2.073***	78.292***	5.485***	3.351**	2.095***	75.979***
	(0.157)	(0.371)	(0.113)	(2.758)	(1.411)	(1.055)	(0.103)	(2.464)
Adj. R2	0.464	0.218	0.143	0.093	0.260	0.253	0.152	0.093
N	85,281	85,281	85,281	85,281	85,281	85,281	85,281	85,281

Note: Models exclude students who were below or above 18, the traditional age of first-time college enrollment. Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Binary indicator of first-generation equals one for students who have no degree-holding parents or only one degree-holding parent. The reference category is non-first-generation students, i.e. those with two degree-holding parents. Standard errors clustered by institution and are in parentheses.
* p<0.05 **p<0.01 ***p<0.001.

Table 2- 17 Estimates Excluding Students who are Below or Above Traditional Age; Categorical Measure of First-Generation Status

	Panel A: Three-Category Measure of First-Generation Status							
	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
Neither Parent Has Degree	-0.070***	-0.255***	-0.073***	-1.359***	-0.110	-0.316**	-0.072***	-1.391***
	(0.013)	(0.036)	(0.007)	(0.226)	(0.123)	(0.088)	(0.007)	(0.235)
One Parent No Degree	-0.055***	-0.196***	-0.066***	-1.070***	-0.006	-0.170	-0.062***	-1.014***
	(0.008)	(0.038)	(0.010)	(0.256)	(0.117)	(0.099)	(0.010)	(0.236)
Constant	7.332***	5.591***	2.074***	78.354***	5.507***	3.383**	2.097***	76.060***
	(0.158)	(0.368)	(0.112)	(2.734)	(1.408)	(1.054)	(0.102)	(2.441)
Wald Test								
Pr(Neither Parent College = One Parent)	0.261	0.144	0.497	0.215	**0.010**	**0.013**	0.314	0.086
Adj. R2	0.464	0.218	0.143	0.093	0.260	0.253	0.152	0.093
N	85,281	85,281	85,281	85,281	85,281	85,281	85,281	85,281

Panel B: Four-Category Measure of First-Generation Status								
	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
Neither Parent Has Degree	-0.070***	-0.255***	-0.073***	-1.359***	-0.111	-0.317**	-0.072***	-1.390***
	(0.013)	(0.036)	(0.007)	(0.226)	(0.123)	(0.088)	(0.007)	(0.235)
Only Mother Has Degree	-0.069***	-0.206***	-0.063***	-1.077**	0.114	-0.066	-0.058***	-1.137***
	(0.012)	(0.048)	(0.011)	(0.317)	(0.129)	(0.106)	(0.011)	(0.290)
Only Father Has Degree	-0.043**	-0.187***	-0.069***	-1.063**	-0.113	-0.262*	-0.065***	-0.905**
	(0.013)	(0.046)	(0.013)	(0.305)	(0.113)	(0.105)	(0.012)	(0.274)
Constant	7.334***	5.592***	2.074***	78.355***	5.494***	3.371**	2.096***	76.074***
	(0.158)	(0.367)	(0.112)	(2.733)	(1.408)	(1.055)	(0.102)	(2.439)
Wald Tests								
Pr(Neither College = Mother Only)	0.917	0.246	0.327	0.262	**0.000**	**0.001**	0.197	0.260
Pr(Neither College = Father Only)	0.139	0.207	0.746	0.364	0.959	0.393	0.601	0.110
Pr(Mother Only = Father Only)	0.204	0.726	0.642	0.969	**0.000**	**0.013**	0.554	0.459
Adj. R2	0.464	0.218	0.143	0.093	0.260	0.253	0.152	0.093
N	85,281	85,281	85,281	85,281	85,281	85,281	85,281	85,281

Note: Models exclude students who were below or above 18, the traditional age of first-time college enrollment. Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Panel A shows results using a categorical variable of first-generation status with two different categories of first-generation students (no degree-holding parents and one degree-holding parent), and Panel B shows results using a categorical variable with three categories of first-generation (no degree-holding parents, or, only mother or only father is degree-holding). The reference category is non-first-generation students, i.e. those with two degree-holding parents. Tests of regression coefficient equivalence (Wald Tests) show whether differences between estimated coefficients between each category of first-generation student are statistically significant (bolded). Standard errors clustered by institution and are in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Table 2- 18 Estimates Excluding Students Who Dual-Enroll in High School; Binary Measure of First-Generation Status

	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
At Least One Parent No Degree	-0.051***	-0.230***	-0.076***	-1.340***	-0.054	-0.249**	-0.072***	-1.267***
	(0.009)	(0.027)	(0.008)	(0.181)	(0.099)	(0.071)	(0.007)	(0.193)
Constant	7.340***	6.068***	2.268***	81.775***	6.470***	4.489***	2.289***	78.880***
	(0.152)	(0.281)	(0.089)	(2.122)	(1.182)	(0.974)	(0.083)	(1.832)
Adj. R2	0.533	0.238	0.132	0.088	0.245	0.244	0.140	0.089
N	166,183	166,183	166,183	166,183	166,183	166,183	166,183	166,183

Note: Models exclude students who earned college credit through AP or dual enrollment programs. Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Binary indicator of first-generation equals one for students who have no degree-holding parents or only one degree-holding parent. The reference category is non-first-generation students, i.e. those with two degree-holding parents. Standard errors clustered by institution and are in parentheses.
* p<0.05 **p<0.01 ***p<0.001.

Table 2- 19 Estimates Excluding Students Who Dual Enroll in High School; Categorical Measure of First-Generation Status

	Panel A: Three-Category Measure of First-Generation Status							
	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
Neither Parent Has Degree	-0.063***	-0.252***	-0.077***	-1.404***	-0.112	-0.312***	-0.075***	-1.344***
	(0.011)	(0.031)	(0.008)	(0.196)	(0.094)	(0.066)	(0.008)	(0.211)
One Parent No Degree	-0.038***	-0.206***	-0.074***	-1.273***	0.007	-0.183*	-0.069***	-1.186***
	(0.009)	(0.031)	(0.009)	(0.206)	(0.103)	(0.078)	(0.008)	(0.203)
Constant	7.344***	6.076***	2.269***	81.801***	6.493***	4.514***	2.290***	78.911***
	(0.153)	(0.280)	(0.089)	(2.106)	(1.183)	(0.975)	(0.083)	(1.817)
Wald Test								
Pr(Neither Parent College = One Parent)	**0.030**	**0.124**	0.721	0.452	**0.000**	**0.001**	**0.391**	0.293
Adj. R2	0.533	0.238	0.132	0.088	0.245	0.244	0.140	0.089
N	166,183	166,183	166,183	166,183	166,183	166,183	166,183	166,183

	Panel B: Four-Category Measure of First-Generation Status							
	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
Neither Parent Has Degree	-0.062***	-0.252***	-0.077***	-1.403***	-0.112	-0.313***	-0.075***	-1.343***
	(0.011)	(0.031)	(0.008)	(0.196)	(0.094)	(0.066)	(0.008)	(0.212)
Only Mother Has Degree	-0.050***	-0.237***	-0.079***	-1.452***	0.131	-0.097	-0.072***	-1.416***
	(0.010)	(0.027)	(0.008)	(0.178)	(0.112)	(0.081)	(0.008)	(0.188)
Only Father Has Degree	-0.027	-0.180***	-0.070***	-1.119***	-0.100	-0.257**	-0.067***	-0.989**
	(0.015)	(0.045)	(0.012)	(0.282)	(0.101)	(0.087)	(0.011)	(0.268)
Constant	7.346***	6.080***	2.269***	81.819***	6.480***	4.506***	2.290***	78.934***
	(0.153)	(0.280)	(0.089)	(2.105)	(1.182)	(0.976)	(0.083)	(1.815)
Wald Tests								
Pr(Neither College = Mother Only)	0.352	0.631	0.810	0.787	**0.000**	**0.000**	0.740	0.642
Pr(Neither College = Father Only)	**0.022**	**0.079**	0.494	0.237	0.708	**0.202**	0.382	**0.109**
Pr(Mother Only = Father Only)	**0.185**	0.186	0.422	0.191	**0.000**	**0.014**	0.652	0.084
Adj. R2	0.533	0.238	0.132	0.089	0.245	0.244	0.140	0.089
N	166,183	166,183	166,183	166,183	166,183	166,183	166,183	166,183

Note: Models exclude students who earned college credit through AP or dual enrollment programs. Table shows results from models including school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Panel A shows results using a categorical variable of first-generation status with two different categories of first-generation students (no degree-holding parents and one degree-holding parent), and Panel B shows results using a categorical variable with three categories of first-generation (no degree-holding parents, or, only mother or only father is degree-holding). The reference category is non-first-generation students, i.e. those with two degree-holding parents. Tests of regression coefficient equivalence (Wald Tests) show whether differences between estimated coefficients between each category of first-generation student are statistically significant (bolded). Standard errors clustered by institution and are in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Table 2- 20 Estimates of First-Term Outcomes by First-Generation Status, Conservative Definition

	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
At Least One Parent No Degree	-0.044***	-0.142***	-0.038***	-0.716***	-0.109	-0.209***	-0.038***	-0.699***
	(0.009)	(0.025)	(0.006)	(0.145)	(0.057)	(0.041)	(0.005)	(0.137)
Constant	7.342***	5.888***	2.211***	80.534***	6.594***	4.369**	2.230***	77.716***
	(0.137)	(0.284)	(0.093)	(2.074)	(1.468)	(1.192)	(0.084)	(1.823)
Adj. R2	0.523	0.243	0.139	0.093	0.248	0.253	0.147	0.092
N	189,358	189,358	189,358	189,358	189,358	189,358	189,358	189,358

Note: Tables show estimates using a more conservative definition of first-generation student, specifically, students with no degree-holding parents. Students with at least one degree-holding parent are non-first-generation, along with students with two degree-holding parents. Models include school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Standard errors clustered by institution and are in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Appendix

Table A2- 1 Descriptive Statistics, by FAFSA Filing

	No FAFSA	FAFSA	Difference	P-Value
Demographic Characteristics				
Male	55.17%	43.26%	-0.12	0
Female	44.83%	56.74%	0.12	0
White	79.90%	71.54%	-0.08	0
Black	9.41%	18.82%	0.09	0
Latinx	3.52%	2.87%	-0.01	0
Asian	2.74%	1.99%	-0.01	0
Other	4.42%	4.97%	0	0
Non-Citizen	2.11%	1.15%	-0.01	0
U.S. Citizen	97.89%	98.85%	0.01	0
Academic Preparedness				
ACT Composite – Continuous	20.68	21.57	0.89	0
ACT Composite (Bottom 25%)	27.73%	24.07%	-0.04	0
ACT Composite (25-50%]	27.13%	25.73%	-0.01	0
ACT Composite (50-75%]	18.96%	21.90%	0.03	0
ACT Composite (Top 25%)	15.59%	23.72%	0.08	0
Missing ACT Composite	10.59%	4.59%	-0.06	0
Never Dual Enrolled	72.93%	67.50%	-0.07	0
Dual Enrolled	27.07%	32.50%	0.07	0
N Observations	147,668	1,052,900		

Note: Table shows first-term difference in means for non-FAFSA filers (column 1) and FAFSA filers (column 2) between 2010/11– 2017/18. Columns 3 and 4 show the difference and p-value from two-sided t-tests of mean equivalence. Students in the sample include students who are first-time, first-year students enrolled in Tennessee public two- or four-year colleges and universities (excluding Tennessee Career and Technical (TCAT) colleges), who are between ages 17 and 24 and are Tennessee residents.

Table A2- 2 Estimates of First-Term Outcomes by First-Generation Status (Binary Measure), Conditioning Credits Earned by Credits Attempted

	Term		Cumulative	
	Credits Earned	Credits Earned (Adjusted)	Credits Earned	Credits Earned (Adjusted)
At Least One Parent No Degree	-0.220***	-0.179***	-0.218*	-0.190***
	(0.023)	(0.023)	(0.086)	(0.028)
Constant	5.978***	0.233	4.418**	-1.210***
	(0.287)	(0.447)	(1.159)	(0.315)
Adj. R2	0.243	0.331	0.253	0.669
N	189,358	189,358	189,358	189,358

Note: Table compares estimates of credits earned from the original model in Table 2-3 with models adjusting credits earned by credits attempted. Models include school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Binary indicator of first-generation equals one for students who have no degree-holding parents or only one degree-holding parent. The reference category is non-first-generation students, i.e. students with two degree-holding parents. Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Table A2- 3 Estimates of First-Term Outcomes by First-Generation Status (Categorical Measures), Conditioning Credits Earned by Credits Attempted

	Panel A: Three-Category Measure of First-Generation Status			
	Term		Cumulative	
	Credits Earned	Credits Earned (Adjusted)	Credits Earned	Credits Earned (Adjusted)
Neither Parent Has Degree	-0.242***	-0.192***	-0.286**	-0.205***
	(0.027)	(0.024)	(0.081)	(0.030)
One Parent No Degree	-0.197***	-0.166***	-0.150	-0.175***
	(0.028)	(0.027)	(0.089)	(0.031)
Constant	5.986***	0.238	4.444***	-1.204***
	(0.285)	(0.444)	(1.159)	(0.314)
Wald Test				
Pr(Neither Parent College = One Parent)	0.110	0.257	**0.000**	0.226
Adj. R2	0.243	0.331	0.253	0.669
N	189,358	189,358	189,358	189,358

	Panel B: Four-Category Measure of First-Generation Status			
	Term		Cumulative	
	Credits Earned	Credits Earned (Adjusted)	Credits Earned	Credits Earned (Adjusted)
Neither Parent Has Degree	-0.242***	-0.192***	-0.286**	-0.205***
	(0.027)	(0.024)	(0.081)	(0.030)
Only Mother Has Degree	-0.232***	-0.191***	-0.054	-0.198***
	(0.027)	(0.026)	(0.099)	(0.033)
Only Father Has Degree	-0.167***	-0.143***	-0.233*	-0.155***
	(0.039)	(0.035)	(0.090)	(0.037)
Constant	5.990***	0.241	4.435***	-1.202***
	(0.285)	(0.444)	(1.159)	(0.314)
Wald Tests				
Pr(Neither College = Mother Only)	0.739	0.983	**0.000**	0.804
Pr(Neither College = Father Only)	**0.047**	0.119	0.206	0.131
Pr(Mother Only = Father Only)	0.107	0.158	**0.007**	0.204
Adj. R2	0.243	0.331	0.253	0.669
N	189,358	189,358	189,358	189,358

Note: Table compares estimates of credits earned from the original model in Table 2-3 with models adjusting credits earned by credits attempted Models include school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Panel A shows results using a categorical variable of first-generation status with two different categories of first-generation students (no degree-holding parents and one degree-holding parent), and Panel B shows results using a categorical variable with three categories of first-generation (no degree-holding parents, or, only mother or only father is degree-holding). The reference category is non-first-generation students, i.e. those with two degree-holding parents. Tests of regression coefficient equivalence (Wald Tests) show whether differences between estimated coefficients between each category of first-generation student are statistically significant (bolded). Standard errors clustered by institution and are in parentheses.

* p<0.05 **p<0.01 ***p<0.001.

Table A2- 4 Estimates of First-Term Outcomes by First-Generation Status (Binary Measure), Huber-White Standard Errors

	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
At Least One Parent No Degree	-0.052***	-0.220***	-0.070***	-1.255***	-0.032	-0.218***	-0.066***	-1.182***
	(0.008)	(0.017)	(0.005)	(0.118)	(0.025)	(0.028)	(0.005)	(0.111)
Constant	7.357***	5.978***	2.244***	81.102***	6.555***	4.418***	2.260***	78.236***
	(0.051)	(0.107)	(0.032)	(0.769)	(0.150)	(0.162)	(0.030)	(0.727)
Adj. R2	0.523	0.243	0.140	0.093	0.248	0.253	0.148	0.093
N	189,358	189,358	189,358	189,358	189,358	189,358	189,358	189,358

Note: Models include school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Binary indicator of first-generation equals one for students who have no degree-holding parents or only one degree-holding parent. The reference category is non-first-generation students, i.e. students with two degree-holding parents. Robust standard errors in parentheses.
* p<0.05 **p<0.01 ***p<0.001.

Table A2- 5 Estimates of First-Term Outcomes by First-Generation Status (Categorical Measures), Huber-White Standard Errors

	Panel A: Three-Category Measure of First-Generation Status							
	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
Neither Parent Has Degree	-0.064***	-0.242***	-0.072***	-1.322***	-0.094***	-0.286***	-0.069***	-1.261***
	(0.009)	(0.020)	(0.006)	(0.139)	(0.028)	(0.032)	(0.005)	(0.131)
One Parent No Degree	-0.040***	-0.197***	-0.068***	-1.188***	0.030	-0.150***	-0.062***	-1.102***
	(0.009)	(0.020)	(0.006)	(0.136)	(0.028)	(0.032)	(0.005)	(0.129)
Constant	7.362***	5.986***	2.245***	81.128***	6.579***	4.444***	2.261***	78.267***
	(0.051)	(0.108)	(0.032)	(0.770)	(0.150)	(0.162)	(0.030)	(0.727)
Wald Test								
Pr(Neither Parent College = One Parent)	**0.006**	**0.027**	0.413	0.347	**0.000**	**0.000**	0.195	0.235
Adj. R2	0.523	0.243	0.140	0.093	0.248	0.253	0.148	0.093
N	189,358	189,358	189,358	189,358	189,358	189,358	189,358	189,358

	Panel B: Four-Category Measure of First-Generation Status							
	Term Credits				Cumulative Credits			
	Attempted	Earned	GPA	Percent Earned	Attempted	Earned	GPA	Percent Earned
Neither Parent Has Degree	-0.064***	-0.242***	-0.072***	-1.321***	-0.095***	-0.286***	-0.069***	-1.260***
	(0.009)	(0.020)	(0.006)	(0.139)	(0.028)	(0.032)	(0.005)	(0.131)
Only Mother Has Degree	-0.052***	-0.232***	-0.073***	-1.402***	0.168***	-0.054	-0.065***	-1.348***
	(0.011)	(0.026)	(0.007)	(0.176)	(0.036)	(0.041)	(0.007)	(0.166)
Only Father Has Degree	-0.030**	-0.167***	-0.063***	-1.001***	-0.091**	-0.233***	-0.059***	-0.887***
	(0.011)	(0.024)	(0.007)	(0.167)	(0.034)	(0.039)	(0.007)	(0.157)
Constant	7.363***	5.990***	2.246***	81.148***	6.567***	4.435***	2.262***	78.290***
	(0.051)	(0.108)	(0.032)	(0.770)	(0.150)	(0.162)	(0.030)	(0.727)
Wald Tests								
Pr(Neither College = Mother Only)	0.270	0.695	0.958	0.651	**0.000**	**0.000**	0.573	0.605
Pr(Neither College = Father Only)	**0.001**	**0.002**	0.191	0.062	0.901	0.161	0.139	**0.021**
Pr(Mother Only = Father Only)	0.091	**0.030**	0.262	0.053	**0.000**	**0.000**	0.462	**0.018**
Adj. R2	0.523	0.243	0.140	0.093	0.248	0.253	0.148	0.093
N	189,358	189,358	189,358	189,358	189,358	189,358	189,358	189,358

Note: Models include school year, institution, and major fixed effects, as well as controls for students' demographic characteristics, academic preparedness, access to financial resources, and enrollment type. Panel A shows results using a categorical variable of first-generation status with two different categories of first-generation students (no degree-holding parents and one degree-holding parent), and Panel B shows results using a categorical variable with three categories of first-generation (no degree-holding parents, or, only mother or only father is degree-holding). The reference category is non-first-generation students, i.e. those with two degree-holding parents. Tests of regression coefficient equivalence (Wald Tests) show whether differences between estimated coefficients between each category of first-generation student are statistically significant (bolded). Robust standard errors in parentheses.

* p<0.05 **p<0.01 ***p<0.001.

Chapter 4

The Promise of Free: Changes in First-Generation Students' Postsecondary Outcomes After the Initiation of a Statewide Scholarship and Mentoring Program

The benefits of attaining postsecondary credentials are numerous, both for the individual and to society at large (Calahan et al., 2018; Perna, 2006; Trostel, 2015). Degree-holders experience significantly higher earnings, higher rates of employment, greater health insurance benefits, retirement plan contributions, and increased job security (Trostel, 2015). However, for first-generation college students, accessing these benefits of higher education is quite challenging. In addition to fewer academic, financial, and informational resources, first-generation students also have less access to cultural and social capital around college-going—knowledge students typically receive from degree-holding parents—which results in less access to information around how to navigate the college application and enrollment process (Adelman, 1993; Atherton, 2014; Bui, 2002; Choy, 2002; Dennis et al., 2005; Engle, 2007; Inman & Mayes, 1999; Ishitani, 2006; Orbe, 2004; Stephens et al., 2012; Terenzini et al., 1996; Wildhagen, 2015). Consequently, first-generation students are less likely to enroll in college and face more challenges when doing so (Cataldi, 2018; Choy, 2002; Wilbur & Roscigno, 2016). When enrolled, first-generation students have lower GPAs and rates of graduation (D'Amico & Dika, 2013; Martinez et al., 2009; Terenzini et al., 1996).

As a way to support students during the difficult transition to postsecondary education, a growing number of states are implementing "free college", "place-based", or "Promise" programs. As of 2020, there were over 288 promise programs across 41 states (Perna & Leigh, 2020). College promise programs offer an encouraging solution to improve first-generation students' access to postsecondary education at scale (Perna, 2015; Perna et al., 2017; Perna &

Riepe, 2016). By offering participating students financial aid, local and state-run promise programs reduce burdens for students, with the ultimate goal of supporting higher education attainment in a given region (Andrews et al., 2010; Gurantz, 2020; Perna & Riepe, 2016; Wardrip et al., 2018). In addition to providing financial aid, promise programs create a wealth of additional benefits for potential applicants, such as encouraging students to file the FAFSA, requiring students to maintain a certain high school or college GPA, and providing students with information about college enrollment. In this way, promise programs help facilitate access to both financial and informational resources for all potential students, not just those who receive funding. Promise programs are thus particularly well-positioned to support first-generation students, who often lack sufficient financial and information resources and who face the greatest burdens when enrolling (Perna, 2015; Perna et al., 2017; Perna & Riepe, 2016).

The Tennessee Promise (TN Promise) is among a handful of programs nationwide that provide both financial and information supports to ease students transition to college. Initiated in 2013, TN Promise is a scholarship and mentoring program providing a last-dollar scholarship for eligible high school students to attend any Tennessee community or technical college tuition-free along with providing one-on-one mentorship to help students navigate the college process (*TN Promise Handbook 2017-2018*, 2018). With the inception of this program, Tennessee became the first state in the nation to offer a statewide tuition program for high school graduates.

While the primary goal of the TN Promise is to provide students with financial resources and informational supports around college-going, the program arguably contributes much more to students statewide. The program required students to complete a FAFSA to apply for Promise funds, thereby increasing the number of students who file the FAFSA and receive federal financial aid that they would have qualified for, but otherwise would not have received by not filling out the form. Additionally, community partners statewide recruited mentors for potential applicants, created informational resources (e.g. pamphlets, websites, workshops), and encouraged high school seniors across the state to apply for Tennessee Promise. Finally, in guaranteeing that college in Tennessee is free to all eligible students, the initiation of the Tennessee Promise "fundamentally…change[d] the conversation about going to college", according to Mike Krause, the Executive Director of the Tennessee Higher Education Commission (Krause, 2018; Long, 2018). By widely advertising the promise of attending college tuition-free, Promise programs prompted policymakers, educators, community members, and importantly, high school students, to re-define who college is "for", generating a larger cultural shift in college-going.

This study aims to measure differences in first-generation students' postsecondary outcomes following the initiation of the Tennessee Promise. Drawing from a rich, administrative dataset containing detailed information on student enrollment, the study uses an interrupted time series (ITS) strategy to estimate the relationship between the initiation of the TN Promise program and first-generation students' first-term credit and GPA outcomes for students enrolling in public two- or four-year colleges. This study hypothesizes that first-generation students, who have the most to gain from the financial, information, and cultural resources facilitated by Promise, may have improved outcomes following the initiation of Promise, irrespective of their eventual participation in the program. This study asks the following:

1. How does the composition of first-generation and non-first-generation students change following the initiation of the Tennessee Promise?
2. To what extent do the first-term postsecondary outcomes of first-generation students differ following the initiation of the Tennessee Promise? How do differences in outcomes for first-generation students compare to those of non-first-generation students?

3. To what extent do differences vary for first-generation students enrolled in community colleges and first-generation students enrolled in four-year colleges?

An examination of the change in composition of students following the initiation of TN Promise reveals that, following 2015, first-generation students who enrolled in college were less academically prepared and less financially resourced, compared to their non-first-generation peers. ITS estimates show the initiation of the TN Promise is associated with an increase in first-generation students' first-term credits attempted and credits earned and an overall decrease in their first-term GPA. These changes appear somewhat greater for first-generation students than their non-first-generation peers and are concentrated in community colleges. Taken together, results indicate that additional supports are needed for first-generation students during their first term of enrollment. Findings from this study offer a first look at the role promise programs can play in enhancing first-generation students' opportunities to access higher education.

Tennessee Context

Background on Tennessee Promise

To be eligible to apply for the TN Promise program (to have "Promise-potential"), students must be high school seniors who graduate from a Tennessee high school, students who complete a Tennessee home school program, or, Tennessee residents who obtain a General Education Development (GED) or High School Equivalency Test (HiSet) diploma (Kramer, 2020). Students must also be U.S. citizens and file the FAFSA by the January deadline of their senior year. Students submit an application in November of their senior year of high school to participate in the Promise program. After the Tennessee Promise program was initiated in 2013, graduating seniors from the class of 2015 became the first class to apply for TN Promise. These students began their application process in the fall of 2014. The Tennessee Promise program is still in place and will enroll its sixth cohort in the spring of 2020.

To recruit students, the Tennessee Higher Education Commission (THEC), the Tennessee Student Assistance Corporation (TSAC) and other state partners conduct outreach and work with high school counselors. TSAC staff hold TN Promise and FAFSA application workshops and conduct financial aid presentations in almost all counties. Volunteers from THEC, TSAC, nonprofit partners, and higher education institutions also visit high schools to help students complete the FAFSA prior to the TN Promise deadline (Tennessee Higher Education Commission, 2019). Of the first three cohorts of high school seniors eligible to apply for the TN Promise, 57,000-60,000 students completed the application each year, representing about 80-85 percent of all Tennessee high school seniors in a given year (Kramer, 2020; Tennessee Higher Education Commission, 2019b).

Students must meet additional criteria to actually receive funding. After submitting an application, students must also attend mandatory informational meetings through the spring of their senior year, communicate with their assigned volunteer mentor, and complete eight hours of volunteer work prior to enrolling full-time in an eligible Tennessee public two- or participating four-year university in the fall following high school graduation. In this study, students who complete all of the above requirements are referred to as "Tennessee Promise Students" (TPS) (Tennessee Higher Education Commission, 2018). Of the students who applied for the program, only 28 percent (approximately 16,000-17,000 students per year) ultimately completed all of the above steps to become eligible to receive aid (Tennessee Higher Education Commission, 2019). To maintain participation in the program, students must complete their FAFSA form each year, continue to participate in the mentoring program, maintain a minimum 2.0 GPA, and perform eight hours of community service prior to each term the award is received (Kramer, 2020; Tennessee Higher Education Commission, 2017, 2018, 2019b).

As a last-dollar scholarship, TN Promise funding is applied after students receive aid from other sources, including the federal Pell Grant and state gift aid (i.e. Tennessee Education Lottery Scholarship awards). TN Promise funding is paid after all federal and state gift aid is applied to a student's total tuition and mandatory fees. Of the students eligible to receive aid each year, just under half received Pell funding, over half received a Tennessee merit-based award (HOPE, ACCESS, GAMS, Aspire), and over a third received funding from the need-based Tennessee State Assistance Award (TSAA) (Tennessee Higher Education Commission, 2018). After all additional aid was applied, Tennessee Promise Students received an average of $500-600 per semester.[28] A student is eligible to receive TN Promise funds until he or she has earned an associate's degree or a TCAT diploma, or until the student has completed five semesters at an eligible postsecondary institution (provided the student maintains his or her eligibility) (Tennessee Higher Education Commission, 2018).

Tennessee Promise facilitated access to information on college access using several avenues. High school seniors received communication about the TN Promise via email or in-person contact from nonprofit-based counselors through partners like tnAchieves. Once students submit their application, they are paired with a mentor who guides them through the postsecondary application and enrollment process. Mentors attend mandatory mentor/student meetings facilitated by the state's nonprofit partners to support their high school mentees in applying for postsecondary opportunities. Mentors invest 10-15 hours assisting their 5-10 high school mentees. Mentors are required to contact their assigned students at least once every two

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[28] Data on the number of Promise-eligible students receiving some aid or no aid is not available.

weeks from March through December (*Volunteer to Mentor - Tennessee Promise*, 2019). Following graduation, tnAchieves begins sending students twice-monthly text messages with helpful reminders, tips, and information to support with the summer transition and through students' first year of college (Kramer, 2020).

Benefits of the Tennessee Promise as an Intervention for First-Generation Students

The intervention examined in this study is the initiation of the Tennessee Promise. Almost all students with Promise-potential received at least one Promise-related touchpoint during their senior year, ranging from receiving communication from a nonprofit-based counselor, attending a workshop, visiting the TN Promise website, and completing their Promise and/or FAFSA applications, to working with their assigned mentor and receiving text message support from tnAchieves. There is strong evidence that almost all students with Promise-potential engaged with Promise, since over 80 percent of students with Promise-potential applied for the program in any given year, and 90 percent of applicants completed their FAFSA[29] (Kramer, 2020). There is also evidence to suggest that the TN Promise program engaged with large numbers of first-generation students, as 40 percent of TPS are first-generation (defined by THEC as students with no degree-holding parents) (Tennessee Higher Education Commission, 2019).[30]

The cohorts of high school seniors starting from the 2014/15 school year became the first cohorts with exposure to the TN Promise. In receiving communication about the Promise to potentially completing some or all of the Promise application process, students with Promise-potential may have received the following benefits and supports:

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[29] In 2018, 81.7 percent of all first-time filers ages 19 and younger filed the FAFSA in Tennessee (Tennessee Higher Education Commission, 2019b).

[30] As THEC uses a narrower definition of first-generation, the percentage of first-generation students may be higher if a broader definition (like the one used in this study) is used.

- Assistance in filing the FAFSA
- Improved information about college enrollment
- Reduced costs of college attendance
- Mentorship and assistance navigating application process

First-generation students have much to gain from the receipt of financial and information resources. Assistance and encouragement in filing the FAFSA may have helped first-generation students access federal and state financial aid they might otherwise not have received, reducing their cost of college attendance. The numerous sources of information provided by the TN Promise, coupled with workshops and individual mentorship, may have helped first-generation students better navigate the complex application process, from assistance meeting deadlines to help understanding course-taking. Finally, this highly publicized program received recognition from all levels of state government, arguably shifting the conversation about who college is for and how it can be accessed by a diverse population of students. Tennessee's Promise to guarantee any qualifying student the opportunity to gain a two-year degree tuition-free sends a powerful message to stakeholders that a college education can be for all. Furthermore, the initiation of the Promise prompted partner agencies to recruit 9,000 mentors annually and mobilized initiatives at 60 community colleges, career and technical institutions, and four-year institutions across the state urging all students to consider college. As students who face numerous challenges accessing college, the added support from a guidance counselor, teacher, parent, or community mentor may have encouraged first-generation students to pursue higher education opportunities they could not previously afford or access.

Conceptual Framework

"College access" refers to efforts to improve students' pursuit of and transition to postsecondary education, including information on college options, support applying for programs or financial aid, support during enrollment, and advising on coursework, credits, major, and other aspects of postsecondary enrollment. Traditionally, college access has been studied through either the economic model of human capital investment or the sociological model of status attainment (Hossler et al., 1989; Paulsen, 1990). However, Perna (2006) argues for the integration of these models into a holistic conceptual framework of college access. The combined model assumes that students’ educational decisions are determined both by their system of values as well as by economic determinants such as financial resources. Second, a combined model assumes variation in the value of educational attainment across racial, socioeconomic, and other groups. This second assumption is key to explaining differential effects of policies aiming to close gaps in postsecondary attainment across different social groups.

The present study adopts Perna’s (2006) conceptual model for examining college access, as shown in Figure 3-1. At the core of the model is human capital investment in which a student makes decisions based on the expected benefits and costs of college. These cost-benefit calculations are informed by a student’s academic preparation as well as resources (i.e. financial aid or family income). These calculations are further nested within four-contextual layers. The first, innermost layer is a student’s habitus, including demographic characteristics and cultural and social capital. The second layer is the school and community context, which captures how social structures and resources within a school or community (e.g. availability of counselors) may influence college access. The third layer is the higher education context, which explains how postsecondary institutions may influence college access through their geographic proximity to students, the provision of information, and through their recruitment and selection process.

The fourth and outermost layer holds that students' decision-making is shaped by the larger social, economic, and policy context, including financial aid policies (Perna, 2006).

The layered approach captures how aspects in the outer layers may influence factors in the layers below. For example, changes to financial aid policies may send signals to postsecondary institutions, schools, parents, and students about the college admissions process. Thus, a change in policy may alter the information students receive about college from institutions of higher education and their schools and communities and may affect students' cost-benefit calculation of attending college. This framework can be extended to examine outcomes beyond just college enrollment to include college academic outcomes. For example, a student's choice to enroll in a certain number of credit hours may be influenced by their perceived value of taking a certain number of credits as it relates to the length of time until graduation, the amount of time and financial resources they have, and their academic ability, as well as perceived levels of support from their communities, families, and the college itself (Perna, 2015).

Perna's (2006) conceptual model provides a logical framework to guide the present analysis of differences in first-generation and non-first-generation students' first-term outcomes following the implementation of the Tennessee Promise program. As a state-level scholarship and mentoring program intending to change the culture of college-going, the Tennessee Promise program sent a number of different policy signals to postsecondary institutions, schools, parents, community members, and high-school students about who college is for, and the commitment of the state government towards supporting free college access for all students in Tennessee. In addition to encouraging FAFSA filing, the program helped communicate additional information about the college admissions process by pairing of students with mentors, the creation of a website, and through information sessions held for Promise-eligible students. As such, the financial and information resources and cultural shifts created by the TN Promise touch all levels identified in Perna's (2006) conceptual model. In potentially altering students' access to resources, information, and supports, the initiation of the Tennessee Promise may have influenced students' decisions around enrollment, including their academic performance. Moreover, in recognizing that subgroups of students have different considerations and values, this framework can capture how first-generation students may perceive and respond differently to messaging and policy signals from the Tennessee Promise compared to their peers.

Literature

Factors Affecting First-Generation Students' College Access

Scholars contend that differences in first-generation and non-first-generation students' pre-college and college outcomes stem from differences in first-generation students' cultural and social capital (Bean, 1983; Bourdieu, 1986; Coleman, 1988; Pascarella et al., 2004; Tinto, 1993; Tobolowsky et al., 2017; Toutkoushian et al., 2019). Cultural capital is the "degree of ease and familiarity that one has with the 'dominant' culture of a society", while social capital comprises the relationships between individuals that facilitate the transaction of other capital, like cultural, human, or even additional social capital (Berger, 2000; Bills, 2003; Bourdieu, 1977, 1986, 1986; Coleman, 1988; Field, 2016; Jæger & Karlson, 2018; Lin, 2002; Møllegaard & Jæger, 2015; Moschetti & Hudley, 2015; Tan, 2017). Parents who have college degrees may have greater familiarity with college expectations and may familiarize their children with these norms and expectations from an early age, giving their children an advantage (Martinez et al., 2009; Palbusa & Gauvain, 2017). In contrast, parents who do not hold a college degree may be less familiar with college life and might not have the experience, knowledge, or connections to help their students navigate the process, leaving their children comparatively disadvantaged (Martinez et al., 2009; Palbusa & Gauvain, 2017). Furthermore, college-educated parents have greater financial resources that can be leveraged to alleviate the costs associated with college, decreasing their children's' financial burden (Engle, 2007; Terenzini et al., 1996).

Prior work has examined several factors that affect first-generation students' college access and success once enrolled, including (1) information about college, (2) college costs and access to financial resources and (3) academic preparedness, and (4) demographic characteristics (Atherton, 2014; Barry et al., 2009; D'Amico & Dika, 2013; Engle, 2007; Inman & Mayes, 1999; Johnson, 2008; Martinez et al., 2009; Page & Scott-Clayton, 2016; Pascarella et al., 2004; Perna, 2006; Schwartz et al., 2017; Terenzini et al., 1996; Tobolowsky et al., 2017; Toutkoushian et al., 2019; Wilbur & Roscigno, 2016). While each of these components play a role in college access for all first-generation students, the former two, which are addressed by promise programs, are discussed in detail below.

Information about College

A chief barrier to college access is the challenge of processing and using information about college. Students may lack sufficient information about how the college admissions process works or may not be able to make sense of available information. This prevents students from "engaging optimally" with the college admissions process (Page & Scott-Clayton, 2016, p. 10). Examples of information students need to access college includes information on how to complete the streams of paperwork required, the importance of campus tours, knowing which courses to take, and how to complete college coursework with success. Once enrolled, students may continue to need additional supports to access and understand information about college completion. First-generation students in particular may face additional challenges, such as a lack of sufficient institutional, family, and peer supports during school (Adelman, 1993; Dennis et al., 2005; Ishitani, 2006; Orbe, 2004; Stephens et al., 2012). A longitudinal study of first-generation students of color found that a lack of peer support was negatively related to students' adjustment in college and GPA (Dennis et al., 2005). Another report investigated the role of parent-student communication in students' transition to college. Using survey data on first-year students, the study found that, though the frequency of communication with parents did not significantly differ between the two groups, first-generation students reported the communication to be lower in quality and helpfulness. The quality of the communication was positively associated with students' first year GPAs (Palbusa & Gauvain, 2017).

Financial Resources

A second barrier is college costs and a lack of access to financial resources. College tuition is a significant barrier to college access since tuition has increased over time, while family incomes have remained stagnant for over a decade. Obtaining financial aid requires having insight and information about the process, such that many students who would qualify for aid fail to access funding due to a lack of procedural knowledge. Even if federal or state aid is obtained, it is no longer sufficient to cover college costs (Perna, 2010, 2015), and is less likely to meet the needs of students in need (Doyle, 2010). First-generation students in particular come from households with fewer financial resources and greater financial constraints (Atherton, 2014; Bui, 2002; Choy, 2001; Inman & Mayes, 1999; Lee et al., 2004; McCarron & Inkelas, 2006; Terenzini et al., 1996). Terenzini et al. (1996) and Bui (2002) find that first-generation students are more likely to come from lower socioeconomic backgrounds and have more dependents, indicating that first-generation college students have access to fewer financial resources and have greater financial responsibilities.

Measuring the Impact of Promise Programs

Most current work on promise programs traditionally examines the following post-secondary outcomes: enrollment (Bartik et al., 2017; Bozick et al., 2015; Bruce & Carruthers, 2014, 2014; Daugherty & Gonzalez, 2016; Gonzalez et al., 2014; Page & Iriti, 2016; Swanson & Ritter, 2018), college choice (Andrews et al., 2010; Bozick et al., 2015; Daugherty & Gonzalez, 2016; Iriti et al., 2018), and persistence (Bartik et al., 2017; Carruthers & Fox, 2016; Daugherty & Gonzalez, 2016; Gonzalez et al., 2011; Page et al., 2018). Studies of promise programs have found that eligibility or participation in a promise program is typically associated with positive outcomes in terms of students' postsecondary success. For example, studying the impact of the Pittsburg Promise program on students' college enrollment, college choice, and persistence, Page, Iriti, Lowry, and Anthony (2018) find that Promise-eligible students graduating from Pittsburg public schools are about 5 percentage points more likely to enroll in college, 10 percentage points more likely to enroll in a Pennsylvania institution, and 4-7 percentage points more likely to persist into their second year. In examining students' school choice sets, a study of the Kalamazoo Promise found that the Promise increased the likelihood that students from Kalamazoo Public Schools considered attending state schools in Michigan. The authors argue that the reduced price for students to attend Michigan's public colleges incentivized Kalamazoo Promise-eligible students to consider these schools (Andrews et al., 2010).

Other studies find mixed results when examining the impact of a promise program. Using data from the New Haven Promise program, Daugherty and Gonzalez (2016) find a positive impact of the Promise on public college enrollment with a regression discontinuity design. But trends in enrollment for eligible graduates do not appear significantly different than those of ineligible high school graduates when using a differences-in-differences strategy.

Only two known studies have examined credit accumulation (Bartik et al., 2017; Carruthers & Fox, 2016; Swanson et al., 2016). A recent study by Carruthers and Fox (2016) examines Knox Achieves, the precursor to TN Promise, implemented in Knox County, Tennessee. In addition to examining college enrollment and persistence, the authors (2016) also examine the effect of Knox Achieves on the number of cumulative credits earned by students participating in the program within two years of graduating high school. Carruthers and Fox (2016) find that take-up of the Knox Achieves scholarship was associated with positive gains in credits, estimating that Knox Achieves participants earned almost 7 credits more than their matched high school peers who did not participate in the program. Importantly, the study's findings suggest that both the scholarship and mentoring components of the program contributed to these gains. Bartik, Hershbein, and Lachowska (2017) examine credits attempted within four years of high school graduation for students eligible for the Kalamazoo Promise program. This study does not use actual data on credits taken by students, but rather estimates the number of credits students were taking using students' full-time or part-time status and information on the number of semesters attended. The authors find that, after eight semesters, Promise-eligible students attempted about 6.5 more credits on average, roughly equivalent to two additional classes.

A few studies examine the impact of promise programs on socially significant student subgroups. While some studies find gains in enrollment and completion for students of color and students from low socioeconomic backgrounds enrolled in the EL Dorado, Oregon and Kalamazoo Promise programs (Bartik et al., 2017; Gurantz, 2020; Swanson & Ritter, 2018), others find no significant differences in outcomes from participation in the Pittsburg Promise by race, sex, language-learner status, or socioeconomic status (Bozick et al., 2015; Page et al., 2018). However, no known studies have examined the relationship between the initiation of a Promise program on first-generation students. This study seeks to add to the body of literature examining promise programs by examining the post-Promise outcomes of first-generation students in a statewide program. In estimating differences in credits attempted and earned, this study examines differences in proximal, granular outcomes that have been less frequently studied in the context of promise programs.

Empirical Strategy

Data

This project uses a unique Tennessee administrative dataset obtained through the Tennessee Postsecondary Evaluation and Analysis Research Lab (TN-PEARL), a research-practice partnership between Vanderbilt University's Peabody College of Education, the University of Tennessee's Boyd Center for Business and Economic Research, and the Tennessee Higher Education Commission (THEC). Data contain longitudinal information on students enrolling in Tennessee community colleges and public four-year universities from 2010/11 - 2017/18, including student demographics, term-level information on enrollment, eligibility for financial aid, family financial resources from the FAFSA, and students' precollege test scores.[31] An indicator is also available identifying "Tennessee Promise Students" (TPS). These are students who complete all requirements of the Tennessee Promise program and enroll full-time in a Promise-eligible institution between the 2015/16 – 2017/18 school years in the fall falling high school graduation (Tennessee Higher Education Commission, 2019).

[31] In this study, the leading year is used to represent school year. So, "2017" would represent the 2017/18 academic year.

Sample

The analytic sample includes eight cohorts of first-time, first-year students who first enroll in Tennessee community or four-year colleges in the 2010/11 through the 2017/18 school years, who have filed a FAFSA, who have complete information on the outcome and explanatory variables of the study, and who are eligible to apply for participation in Tennessee Promise.[32] Restricting the analysis to include only students who file the FAFSA was necessary to identify students' first-generation status and available financial resources. Of note is the high rate of FAFSA completion in Tennessee. At a filing rate of 82 percent, Tennessee is a leader in FAFSA completion among first-time filing applicants. Since the majority of students in the state apply for federal aid, there is substantively less risk of selection bias from selecting on students who file the FAFSA, though some differences in students who do and do not file a FAFSA exist.[33]

Students with Promise-potential are defined as students who are U.S. citizens, dependents under age 25, and Tennessee residents who enroll in public two-year community colleges or public four-year universities. These students were exposed to Tennessee Promise program implementation and whose outcomes can be measured. First-time, first-year students were

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32 Students with complete information on enrollment, but who do not attempt any credits, were removed from the sample.

33 Since the initiation of Tennessee Promise induced more students to file the FAFSA form, it is important to examine changes in the characteristics of students who filed before and after the initiation of the Promise to determine how students who received federal and state aid may be different in the post-Promise period. Appendix Table A3-1 shows the demographic characteristics and academic preparedness of students who file (Panel A) and do not file the FAFSA (Panel B), before and after the initiation of the Tennessee Promise. Following Promise-initiation, students filing the FAFSA were less likely to be White or Black, and more likely to be Asian or Latinx, compared to those filing before. While there appears to be no differences in the average ACT composite score, slightly more students who scored in the bottom 25th percentile are filing in the post-Promise period.

Non-FAFSA filers after Promise initiation are more likely to be male, Latinx, or Asian, and less likely to be White or Black. They have a slightly higher ACT composite score and are more likely to score in the top 50th percentile. Overall, changes in the demographics of FAFSA and non-FAFSA filers following the initiation of Promise are in the same direction. The main difference is that FAFSA filers have lower academic preparedness than non-FAFSA filers, which could also indicate a lack of other resources and supports. Since only students who file the FAFSA are eligible to apply for the Tennessee Promise, this change in composition may help explain some of lower outcomes observed in this study following the initiation of the Tennessee Promise.

identified using a pre-existing indicator variable in the P20 data.[34] This results in a sample of 187,117 observations capturing students' first-term of enrollment.

Measures

Independent Variables

Post-Promise Level Change. The key indicator is a binary variable equal to 0 in the pre-Promise period (2010/11 – 2014/15) and 1 in the post-Promise period (2015/16 – 2017/18). This indicator can be thought of the change in a given outcome immediately following the initiation of Promise. As this analysis examines first-time, first-year students' outcomes in their first-term of enrollment, the level-change variable is equivalent to cohort exposure to Tennessee Promise.

Pre-Promise Trend. To account for pre-intervention trends in the outcome over time, a pre-trend variable is included. This variable is a continuous measure of time ranging from -4 to 3. Values of -4 to 0 represent each of the pre-Promise years and values of 1 to 3 represent the post-Promise years. The variable is centered on the 2014/15 school year, the year before Promise implementation. The addition of a time trend thwarts the likelihood of spurious relationships (Wooldridge, 2012).

Post-Promise Change in Slope. The post-Promise indicator is interacted with the pre-Promise trend variable as an estimator of the post-Promise change in slope. This variable ranges from 0 to 3, with 0 representing pre-Promise years and values of 1, 2, and 3, representing each of the three post-Promise years.

[34] Some students in the data were high school students participating in the dual-enrollment program in which they took college-level coursework during high school. For these students, dual-enrollment terms were removed such that their first time in the data was during the semester they first enrolled following high school graduation. Finally, some students' first-term of enrollment was summer in which students enrolled part-time. These summer terms were treated similar to dual-enrollment. These summer terms were omitted such that a students' first-term of enrollment was either a fall or spring term. In total, about 4,000 observations were omitted for 1,000 unique students.

First-Generation Status. The FAFSA asks families to provide the highest level of schooling completed by both parents. Families select from the following options: (1) Middle school/Jr. High, (2) High School, (3) College or beyond, or (4) Other/unknown. Using this information, students' first-generation status was operationalized as a binary indicator equaling one when a student had at least one parent who had not completed a college degree. The other/unknown category was treated as non-college-going.[35] This indicator represents students who do not come from households where both parents have college-going capital.

Dependent Variables

The primary dependent variables in this study are students' first-term credits attempted, first-term credits earned, percent credits earned, and first-term GPA. Credits attempted and earned are continuous measures of credits. Percent credits earned is calculated by dividing credits earned by credits attempted.[36] GPA is a continuous measure of GPA points.

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[35] Of the 187,117 observations in the first term of enrollment, the highest education level was unknown for 6 percent of fathers and 9 percent of mothers.

[36] Modeling dependent variables as percentages should be done with caution (Wooldridge, 2012). A percent variable has a binomial distribution, as it measures the percent credits successfully earned out of those attempted. However, such a percent is likely non-linear in the extremes, especially since the range of the variable includes values in the tails (typically, below 20 and above 80 percent). Furthermore, a percent is bounded from 0 to 100 percent, which violates an assumption of linear regression models, namely that the outcome variable is unbounded (Wooldridge, 2012).

Another way to model the percent credits earned variable is to include as the dependent variable the number of credits earned and adjust the outcome by controlling for the number of credits attempted. All tables and figures were estimated replacing the percent credits earned variable with a model predicting term credits earned and adjusting for credits attempted. As an example, main estimates for term credits earned (Tables 3-10 and 3-13) were compared with models estimating term credits earned while adjusting for credits attempted (Appendix Table A3-2 and Appendix Table A3-3). Neither the significance nor the direction of the estimates changed in any way after changing the percent variable to a model conditioning on credits attempted. In most cases, results on coefficients of interest for both the percent variables and the adjusted credits earned models are null. As results were indistinguishable in sign and significance and are mostly null, the percent variable was chosen to include in the main results as it may be more intuitive for some readers to think about credits earned as a percent rather than as conditional on credits attempted.

Control Variables

This study uses four groups of control variables identified in prior literature as related to students' college success, including students' demographic characteristics, level of academic preparedness, access to financial resources, and institutional characteristics.

Demographic Characteristics. Demographic characteristics include students' race and sex. Student race is a categorical variable for whether a student is Black, White, Latinx, Asian, or other race/ethnicity. Student sex is a binary indicator equaling 1 when a student is female and 0 if male.

Academic Preparedness. Academic preparedness captures the academic skills students may have when navigating college and completing collegiate work, such as level of academic readiness, time management skills, motivation, or maturity. Academic preparedness is measured using students' ACT composite score, whether students were ever dual enrolled in postsecondary coursework during high school, and students' age when they first enrolled as first-time, first-year students. ACT composite score is a continuous variable ranging from 1 to 36. Dual enrollment is a binary indicator equal to 1 if a student ever dual enrolled in college coursework during high school and 0 otherwise. Age of first enrollment is a categorical variable for whether a student enrolled for the first time at age 17, at age 18, or between 19-24.

Financial Resources. Students' access to financial resources is measured using data from the FAFSA form, which provides information on students' access to family resources and their eligibility for various federal and state awards and scholarships. Family resource variables include parental expected financial contributions (EFC) towards postsecondary education and students' and parents' adjusted gross income (AGI). EFC is calculated using a formula delineated by the U.S. federal government. This formula considers household size, and parental income, work status, savings, and investments. Households may have an EFC of zero if household income falls below a certain threshold.[37] AGI is reported using information from federal tax forms and includes wages, alimony, Social Security, and business income. Parent and student AGI and parental EFC were log transformed. In a minutia of cases, students or parents had negative incomes or incomes of 0, indicating that individuals experienced financial losses greater than their total yearly income. Since the natural log function is only defined for values greater than 0, values of 0 for parental EFC and parent and student AGI were replaced by 1.

Additionally, binary indicators for students' eligibility for frequently accessed federal- and state-level scholarships and grants were also included. These include measures for whether a student was eligible for the Pell Grant, the Tennessee Student Assistant Award (TSAA), the Tennessee HOPE scholarship, the HOPE Access grant, the Tennessee HOPE Aspire award, and the General Assembly Merit (GAM) scholarship. These indicators denote eligibility, and not necessarily take-up, of the award. The Pell Grant is a federal grant that is awarded to students who meet the government's basic eligibility criteria, amongst other financial, school, and family factors.[38] The TSAA is a state needs-based award for eligible Tennessee high school students. The Tennessee HOPE scholarship is a merit-based scholarship for eligible Tennessee high school students. The Tennessee HOPE Aspire award is awarded to students who are eligible for the Tennessee HOPE scholarship and who have an income less than $36,000. The Tennessee HOPE Access grant is a merit-based scholarship for low-income students who just miss the HOPE scholarship criteria. The GAM is an additional merit-based scholarship that supplements the HOPE scholarship for high-achieving entering first-year students.[39]

37 See here for the EFC formula guide.
38 For more information on needs-based awards, visit the following sites: Pell Grant, TSAA.
39 For information on the Tennessee HOPE scholarships, visit the following sites: HOPE, Aspire, Access, GAM.

Institution and Major. To control for unobserved heterogeneity in student performance, professional goals, and other institution-related factors that may affect student outcomes, fixed effects for institution and major are included. Heterogeneity in student outcomes due to institution of enrollment and major may arise from differences in the required coursework, number of credits, and institutional resources, as well as differences amongst students who choose particular institutions or majors, such as level of rigor, tuition, or geographic distance to home. Students' institution is the public institution of enrollment in their first term. Students in the sample attend one of 22 Tennessee public two- or four-year institutions in their first term. Anywhere from 1.7 percent (approximately 3,000 students) to 12.15 percent (approximately 23,000) of students in the analytic sample attend a given institution during their first term. Students' major is a categorical variable of students' currently declared major in their first term of enrollment. This variable was created by categorizing over 280 major codes into 7 common areas of study.[40]

Analytic Strategy

First, the analysis explores changes in the composition of students enrolling following the initiation of the Tennessee Promise. The pre- and post-Promise differences in demographic, academic preparedness, financial resources, institutional characteristics, and outcomes are calculated using independent two-sided t-tests of mean equivalence. To test the hypothesis that the difference in the pre- and post-Promise means is zero, the below t-statistics is calculated:

[40] First, major CIP codes were grouped into 32 categories using pre-existing identifiers for major. Next, the 32 major categories were collapsed into 7 common areas of study (e.g. liberal arts, business, health, etc.).

$$t = \frac{(\mu_{Post} - \mu_{Pre})}{\sqrt{\frac{s_{Post}^2}{n_{Post}} + \frac{s_{Pre}^2}{n_{Pre}}}}$$

Here, μ_{Pre} and μ_{Post} are the pre- and post-Promise means, respectively, for a given outcome. s_{Pre}^2 and s_{Post}^2 are the variance of the outcome variables in the pre- and post-Promise periods, respectively, and n represents the sample size in each period. Mean values between the pre-and post-Promise periods are considered significantly different if the p-value for the t-statistic is less than 0.05. T-tests are calculated for the full sample, and then separately for non-first-generation and first-generation students. Differences amongst first-generation and non-first-generation students based on their participation as Tennessee Promise Students are also compared.

Next, the analysis turns to estimating the relationship between the initiation of the TN Promise and changes in first-generation students' first-term outcomes. In the absence of experimental data and a suitable control group, an ideal method to answer the research questions in this study is an interrupted time series analysis (ITS) (Moffitt, 1991).[41] An ITS analysis aims to measure the effect of an exogenous intervention (i.e. initiation of Tennessee Promise) while controlling for the underlying trend in the outcome variable over time. A requirement of an ITS analysis is that the outcome variable should be expected to change soon after the implementation of the intervention. Additionally, there must be sufficient observations in the pre-intervention period to determine the functional form of the outcome variable. With a clearly delineated intervention start date as well as four pre-Promise years of data, this analysis meets these criteria.

[41] As the population of students ineligible to apply for the Tennessee Promise is quite different than the population of students who is eligible (e.g. out-of-state students, non-U.S. citizens, those who have enough resources such that they choose not to file the FAFSA), methods requiring a control group such as a differences-in-differences or a comparative interrupted time series were not feasible in this study.

First, naïve ITS models explore model fit using the sample of first-generation and non-first-generation students, as well as the full sample of first-generation and non-first-generation students. Each outcome of interest is regressed on the post-Promise level-change variable as shown in equation 1:

$$y_{it} = \beta_0 + \beta_1 Z_{it} + \epsilon \qquad (1)$$

Here, y is an outcome for individual i in time t. Z_{it} is the binary indicator for post-intervention period and represents whether individual i in time t is in the pre- or post-Promise period, and ϵ represents the random error. β_0 represents the pre-Promise mean in the outcome variable. The coefficient β_1 measures the change in the outcome variable following the start of the intervention. Standard errors are clustered within institution to account for intraclass correlations between students enrolled in the same institution.[42] However, such a model does not account for pre-intervention trends in the outcome variable over time, as added in equation 2:

[42] Standard errors are typically clustered when the observations are not expected to be independent and identically distributed (i.i.d) and are correlated within clusters. However, when fixed effects are also included in the model, the motivation to cluster standard errors is less clear. Scholars like Abadie et al. (2017) and Cameron and Miller (2015) argue for the use of clustered standard errors in a fixed effects model "if either the sampling or assignment varies systematically with groups in the sample" (Abadie et al., 2017, p. 2).

Furthermore, scholars hold that the addition of fixed effects only partially accounts for within-cluster correlations in the error terms, again, making the case to cluster standard errors (Cameron & Miller, 2015). In the present study, assignment to institutions is not random, and both institution and major fixed effects are used, indicating support for the use of errors clustered at the institution level, the level at which autocorrelation is expected. However, Abadie et al. (2017) also argue that clustering when using fixed effects matters if there is heterogeneity in treatment effects (p. 14). A test for serial correlation in the data using the xtserial command rejected the null hypothesis that no serial correlation exists, for all four outcomes. If these results are to be believed, then clustering standard errors is not necessary, and Huber-White robust standard errors would be appropriate. To present the most conservative estimates, this paper presents cluster-robust standard errors in the main analyses. All tables were also re-estimated using Huber-White standard errors. In these models, coefficients that were not significant appear significant, most notably, coefficients on the post-Promise slope-change variable. As an example, the main analysis tables (Tables 10 and 13) with Huber-White standard errors are show in Appendix Table A3- 4 and Appendix Table A3- 5.

$$y_{it} = \beta_0 + \beta_1 Z_{it} + \beta_2 T_t + \epsilon \qquad (2)$$

Equation 2 includes T_t, a continuous variable accounting for the time period. Now, β_0 represents the mean value of the outcome in 2010/11. β_1, the coefficient on Z_{it}, captures the change in the level in the post-Promise period, and β_2, the coefficient on T_t, is the slope of the trend in both the pre- and post-Promise periods.

In some instances, the post-intervention trend may also change. Accordingly, an interaction between T_t and Z_{it} is added, representing a post-Promise slope change, as shown in equation 3:

$$y_{it} = \beta_0 + \beta_1 Z_{it} + \beta_2 T_t + \beta_3 T_t Z_{it} + \epsilon \qquad (3)$$

With the addition of the interaction term, β_2 represents the pre-Promise trend and β_3 represents the estimated change in the slope in the post-Promise period. Exploring naïve model fit explores how patterns in the data are explained by the variables level-change (Z_{it}) , pre-trend (T_t), and the interaction term representing the post-Promise change in slope ($T_t Z_{it}$).

To examine the extent to which outcomes differ for first-generation students following the initiation of Tennessee Promise, two analytic strategies can be used. Models can include interaction terms between the indicator for first-generation student and the level-change and trend variables, or, subgroup models can be estimated for each group. Because models with interaction terms are estimated using the full analytic sample, the power to estimate effects is greater. If covariates operate differently for each group, interacted models may not accurately measure the relationship between a given subgroup and the outcome of interest. In that case, separate models may be preferred, though the reduction in sample may incur a loss in power.

To compare whether coefficients estimated for non-first-generation students are the same as those estimated for first-generation students, a series of Chow tests are conducted. Chow tests examine the equivalence of coefficients for two groups of students by running a model interacting covariates with the binary indicator denoting group membership, and then testing the hypothesis that the difference between interaction terms is jointly zero. If the interaction terms are not jointly significant, this indicates that there is no marginal difference in the relationship between the covariates and the outcome due to participation or non-participation in the group. The test is first conducted on partially interacted models in which the indicator for first-generation students is interacted with only a few covariates, as well as on the fully interacted model, in which the indicator is interacted with all covariates. The test produces an F-statistic and p-value to determine whether covariates are significantly different between first-generation and non-first-generation students. Interaction coefficients that do not differ significantly across the two groups would motivate the use of a pooled model. Conversely, covariates that differ across groups would suggest that there are differences in how covariates function for students in the two groups, motivating the continued use of separate models.

Table 3-1 presents F-statistics and p-values from Chow tests to determine whether coefficients between first-generation and non-first-generation students are equivalent. Each row contains a different outcome. Columns 1 and 2 present results from Chow tests on partially interacted models, which interact the indicator for first-generation status with the level-change and pre-trend covariates (column 1), as well as key predictors of student performance (i.e. parental AGI and EFC, ACT composite score, and the indicator for dual enrollment) (column 2).

Column 3 presents results from fully interacted models. F-tests of coefficient equivalent were conducted for the interacted variables and the indicator for first-generation student. For all but one model, the Chow tests yielded a significant p-value, indicating that the interacted coefficients operate differently between first-generation and non-first-generation students. Results of the Chow tests suggest it is more appropriate to stratify the models by first-generation status instead of estimating pooled models with interaction terms. Accordingly, subgroup models for first-generation and non-first-generation, as well as the full sample of students, are estimated using equation 4:

$$y_{it} = \beta_0 + \beta_1 Z_{it} + \beta_2 T_t + \beta_3 T_t Z_{it} + \beta_4 X_{it} + \gamma + \theta + \epsilon \qquad (4)$$

X_{it} is a vector of covariates representing students' demographic characteristics, academic preparedness, and financial resources, and γ and θ are institution and major fixed effects, respectively. For the full sample of students, β_2 represents the estimated change in outcome for students with similar demographic, academic, and financial characteristics, who are enrolled in the same institution and major. In the subgroup models, the estimates on β_2 and β_3 estimate the level change and post-Promise slope change for each subgroup. F-tests determine whether coefficients between first-generation and non-first-generation students are statistically different from one another. An important check is to examine to what extent results are driven by Tennessee Promise Students who may receive funding and who may be different from non-TPS since they completed all Promise requirements. Models are estimated excluding TPS and compared to main estimates.

As an added check, the post-Promise level-change (Z_{it}) and slope change ($T_t Z_{it}$) variables are replaced by three indicator variables taking values of 1, 2, and 3, for the post-Promise years of 2015, 2016, and 2017, respectively, as shown in equation 5:

$$y_{it} = \beta_0 + \beta_1 Z_{2015it} + \beta_2 Z_{2016it} + \beta_3 Z_{2017it} + \beta_4 T_t + \beta_5 X_{it} + \gamma + \theta + \epsilon \qquad (5)$$

Since the omitted category is the pre-Promise period, coefficients on β_1, β_2, and β_3 represent a level change in a given post-Promise year compared to the pre-Promise period. Wald tests evaluate the equivalence of coefficients on post-Promise year.

Finally, to examine the extent to which post-Promise differences vary for first-generation students enrolled in community colleges compared to those enrolled in four-year colleges, a similar analysis as above is used. Results from Chow tests, displayed in Table 3-2, indicate that predictors operate differently based on institution type, motivating the use of subgroup models to examine outcomes by institution type. Four subgroup models are estimated based on students' first-generation status and institution of enrollment. As above, estimates from models excluding TPS are compared to estimates from the main sample.

Limitations

The analysis is limited in its ability to assess the particular aspects of the TN Promise program that may have contributed to students' postsecondary outcomes. Students had varying degrees of exposure to the Program and could participate in a variety of aspects of the program without formally being selected into the Program to receive funds. While the analysis can observe students who were identified by the state as "Tennessee Promise Students", data on which students received funds and the extent to which non-TPS participated in features of the program are unavailable. Finally, data on students' high school or school district are unavailable, limiting the ability to account for students' pre-college access to academic, financial, and school resources. Since observed associations were concentrated in community colleges, and as community colleges are most frequently attended by students who are from the local community, the analysis hopes the inclusion of institution fixed effects may serve as an adequate substitute to control for students' home districts.

Results

RQ1: How does the composition of first-generation and non-first-generation students change following the initiation of the Tennessee Promise?

Differences Across all Students, Pre- and Post-Promise

A detailed examination of student characteristics before and after the initiation of TN Promise is vital for this analysis. A change in the composition of students would violate a key identifying assumption of an ITS, that, in the absence of the intervention, the pre- and post-intervention groups would be comparable. If the initiation of Promise induced a change in the characteristics of students in the post-Promise group, then it is possible that any post-Promise changes in the outcome variable could be attributed to characteristics of students and not only to the Promise program. For instance, if the funding or encouragement received from Promise caused students to enroll who would not otherwise have attended college due to low academic preparedness, we may expect these students to attempt or earn fewer credits than students who were always planning on attended. Consequently, we may observe a decrease in the average credits completed in the post-Promise period, a decrease partly due to the change in the academic preparedness of the students enrolling following Promise implementation and not necessarily due to the effects of the Promise intervention itself. Differences amongst first-generation and non-first-generation students who complete Promise requirements (i.e. Tennessee Promise Students) may also provide important context on differences in resource access and outcomes based on first-generation status.

First, it is helpful to establish a baseline for changes in student characteristics before and after the initiation of the Tennessee Promise. Table 3-3 displays descriptive statistics for demographic characteristics, academic preparedness, access to financial resources, and institution for the full sample of first-time, first-year students in their first term of enrollment (N=187,117). Columns 1 and 2 display the pre- and post-Promise means, respectively. Column 3 presents the difference in the post-Promise and pre-Promise values, with a positive number indicating an increase and a negative value indicating a decrease. Column 4 contains the p-value from a two-sided t-test of equivalence, testing whether the means in the pre- and post-Promise period are equivalent. Any variable with a p-value below 0.05 is considered to be statistically different in the post-Promise period. Column 5 presents the sample mean for each variable, and columns 6 and 7 show the variable minimum and maximum values, respectively.

In the pre-Promise period (N=113,520), the sample is approximately 55 percent female and 70 percent White. 62 percent of students are first-generation college students who have at least one non-degree-holding parent. Students have an ACT composite score of 20.81. Students enrolling have an AGI of $2,224 and have parents with an average AGI of $68,984 and EFC of $15,775. Over 75 percent of students have parents whose EFC is below $21,000. Just over half of students are eligible for the Pell Grant, and about 47 percent of students are eligible for the HOPE scholarship. 41 percent of students are enrolled in community colleges.

As shown by the differences and p-values in columns 3 and 4, almost all student characteristics are significantly different in the post-Promise period (N=73,597). Students in the post-Promise period are more likely to be female, Latinx, Asian, or other race/ethnicity, and first-generation. Students have lower average ACT composite scores and are less likely to have dual enrolled in high school. Students have access to higher parental AGI and EFC, though there is an increase in students whose parents have EFCs in the top two quartiles. Students are also less likely to be Pell-eligible, but more likely to be eligible for a needs-based grant. Students are far more likely to be enrolled in community college.

Table 3-4 presents statistics for students' first-term post-secondary outcomes. Of the four outcome variables, a statistically significant difference for three variables is observed in the post-Promise period. Students on average attempt 0.6 more credits and earn 0.45 more credits in their first term. However, students have an average GPA 0.03 points lower in the post-Promise period.

Differences Across First-Generation Students, Pre- and Post-Promise

Since the composition of first-generation and non-first-generation students may have been differently affected by the introduction of the TN Promise program, their pre- and post-Promise differences were separately examined, as shown in Table 3-5. Panel A shows characteristics of first-generation students pre- and post-Promise, along with the difference in means and the p-value from a two-sided t-test. Panel B shows these statistics for non-first-generation students. Following the initiation of Promise, first-generation students are more likely to be Black, Latinx, or other race/ethnicity, unlike their non-first-generation peers who are more likely to be White. Notably, following Promise initiation, enrolling first-generation students have significantly lower average ACT composite scores, while non-first-generation students see no such change. Specifically, there are significantly more first-generation students whose ACT composite score falls into the bottom 25 percent of the ACT score distribution, and significantly fewer first-generation students whose scores falls into the top 75 percent of the distribution. While there is a significant increase in the parental AGI and EFC for both groups in the post-Promise period, the increase is much higher for non-first-generation students (increase of $18,419) than first-generation students (increase of $4,058). Correspondingly, there is a decrease in the percent of non-first-generation students who are eligible for the Pell Grant, but there is no change for first-generation students. There are comparable increases in the percent of both non-first-generation and first-generation students enrolling in community college following the initiation of Promise (12 and 11 percentage points, respectively).

Table 3-6 presents similar statistics comparing first-generation and non-first-generation students with respect to changes in the first-term outcomes after Promise initiation. Before the initiation of Promise, non-first-generation students attempted an average of 13.89 credits, while first-generation students attempted an average of 13.39 credits. Non-first-generation students earned about 12.06 credits, while first-generation students earned about 11.13, one credit fewer. Non-first-generation students thus completed on average 86.5 percent of credits they attempt, while first-generation students completed 82.8 percent. Non-first-generation students have higher GPAs (2.72) compared to their first-generation peers (2.54).

Following the initiation of Tennessee Promise, there are significant increases for both groups in terms of credits attempted and earned, though the magnitude of the increase was higher for first-generation students. Neither group sees a significant change in the percent credits earned. Finally, while there is a significant increase in first-term GPA for non-first-generation students of 0.02 points, there is a significant decrease in first-term GPA for first-generations students of 0.04 points, creating an overall average difference of 0.06 GPA points for these two groups of students, increasing the already pre-existing gap in GPA. Figure 3-2 displays trends over time for each of the four outcomes by students' first-generation status. Each graph plots mean values of a given outcome by school year, as well a linear fit line before and after Promise initiation. Full sample means included as a reference.

Differences Across First-Generation Students, by Tennessee Promise Student Status

Of the 73,597 student observations in the post-Promise period, 30 percent of observations, or 21,666 students are Tennessee Promise Students. If first-generation students are defined using the strictest definition, that is, students who have no degree-holding parents, 40 percent of TPS would count as first-generation students (N=8,604). If, instead, the more permissible definition is used, that is, students who have one or no degree-holding parents, then 73.5 percent of TPS would count as first-generation students (N=15,932). THEC uses the strict definition, and documents that 40-45 percent of TPS are first-generation, which corresponds well with the percent observed in the study sample (Tennessee Higher Education Commission, 2019).

Table 3-7 displays differences in first-generation and non-first-generation students in the sample based on their status as TPS in the post-Promise period. For both first-generation and non-first-generation students, TPS are more likely to be White and have lower ACT Composite scores. TPS who are first-generation have access to greater parental financial resources than their non-TPS peers, while TPS who are non-first-generation have less access to financial resources than their non-TPS peers. However, TPS who are non-first-generation have higher ACT scores and greater access to parental financial resources than first-generation TPS. Moreover, as shown in Table 3-8, both first-generation and non-first-generation TPS students have lower outcomes than their non-TPS peers.

Overall, findings from this exploration suggest that following Promise, there is a change in the demographic characteristics, academic preparedness, and financial resources of students enrolling following the initiation of Promise, changes which appear concentrated within first-generation students enrolling post-Promise. The change in composition of students who enroll—in that they are more likely to be of first-generation, Latinx, and have fewer financial resources—suggests that the initiation of Promise may have helped improve access for less advantaged students to access college. As there are some differences in first-generation students and non-first-generation students who are TPS, it is important to also conduct sensitivity analyses excluding TPS for all models.

RQ2: To what extent do the first-term postsecondary outcomes of first-generation students differ following the initiation of the Tennessee Promise? How do differences in outcomes for first-generation students compare to those of non-first-generation students?

Table 3-9 presents the naïve estimates from models with variables for the level-change, the pre-trend, and the post-Promise slope change, with each model adding in an additional variable. Panel A shows estimates from the sample of first-generation students, Panel B estimates from the sample of non-first-generation students, and Panel C estimates from the full analytic sample. Naïve estimates from all three samples follow similar patterns. Models in column 1 for each panel find a significant, positive association between the initiation of Promise and term credits attempted and earned. The addition of the pre-trend in column 2 yields significant, positive coefficients on the level-change variable for models estimating credits attempted, and significant, negative coefficients on the level-change variable for models estimating GPA and percent credits earned. The addition of the pre-trend variable does not yield significant coefficients on models estimating term credits attempted. This pattern holds in the sample on first-generation students and the full sample. When the variable for post-Promise slope change is added in column 3, the level-change variable is significant and positive for term attempted and significant and negative for term GPA. The slope change variable is significant and positive for term credits earned and percent credits earned. This pattern again holds for the first-generation and full samples, suggesting post-Promise may be driven by changes within first-generation students. As the addition of the slope change variable explains some of the variation in the level-change variable across models, the preferred model specification is an ITS model controlling for the level change, pre-intervention trend, and post-intervention change in slope.

As a visual complement to Table 3-9, Figure 3-3 through Figure 3-6 present how the models in the full sample fit the data for each of the naïve model specifications. Mean values for each outcome are plotted with linear predictions from the models in Table 3-9. Panel A shows the linear prediction for a model fit with only the pre- and post-Promise level-change indicator. This model assumes trends are constant in the pre- and post-periods. Panels B and C add predictors for the pre- and post-Promise trends, respectively.

Next, fully specified models controlling for level-change, the pre-intervention trend, and the post-Promise slope change, along with controls for demographic characteristics, academic preparedness, financial resources, and institution and major fixed effects are presented in Table 3-10. For each outcome variable, models are estimated for first-generation and non-first-generation students, as well as the full sample for reference. Panel A presents results from the main samples, while Panel B shows results from the sample excluding Tennessee Promise Students. As shown in Panel A, both first-generation and non-first-generation students attempt more credits post-Promise, with first-generation students attempting 0.65 more credits, and non-first-generation students attempting 0.51 more credits. Wald tests of coefficient equivalence across the two models indicate that the estimated increase for first-generation students is significantly greater than that of non-first-generation students. First-generation students also earn significantly greater credits following Promise initiation, earning approximately 0.48 more credits. There is no observed difference in the post-Promise credits earned for non-first-generation students. Furthermore, though there is no predicted change in non-first-generation students' first-term GPA, there is an associated decrease for first-generation students' GPA by 0.07 points. This is noteworthy as first-generation students' average pre-Promise GPA is already lower than that of their non-first-generation peers. Models predict no change in the percent credits earned post-Promise for either group. No changes in the post-Promise slope are observed.

In Panel B, models excluding Tennessee Promise Students are compared to the main models. A change in the estimated coefficients would indicate that post-Promise changes in outcomes are driven by TPS students. However, no change in estimated coefficients would suggest that post-Promise outcomes are driven by changes to the types of students enrolling or due to changes in behavior due to exposure to the Promise program. The patterns observed in Panel A are maintained for credits attempted and term GPA once TPS are excluded, as shown in Panel B. Both first-generation and non-first-generation students attempt more credits post-Promise, with first-generation students attempting about 0.44 more credits. First-generation students are predicted to earn GPAs 0.07 points lower. While the magnitude of coefficients for credits attempted is smaller, the coefficient for GPA is comparable to the main sample of first-generation students. Results in Panel B demonstrate that, even when excluding students who completed all Promise requirements and who may have received funding from Tennessee, the initiation of Promise altered expected outcomes for first-generation students on average.

Figure 3-7 illustrates the predicted values for first-generation and non-first-generation students from the models shown in Table 3-10. Post-Promise, first-generation students are predicted to attempt slightly more credits than their peers, yet continue to earn fewer credits. Figure 3-7 highlights the decrease in first-generation students' predicted post-Promise GPA (2.49) as compared to that of their peers, which stays relatively stable (2.73).

As a check for robustness, the post-Promise level-change and slope change variables were replaced three indicator variables taking values of 1, 2, and 3, for the post-Promise years of 2015, 2016, and 2017, respectively. The reference category for this variable is the pre-Promise period. As shown in Table 3-11, compared to the pre-Promise period for all three samples, the level-change variable is significant and positive for each post-Promise year for term credits attempted, and is significant and negative in each post-Promise year for percent credits earned. This suggests that the change in these outcomes during each post-Promise year is significantly different that the outcome in the pre-Promise year. Wald tests fail to reject the null hypothesis that the coefficients in the post-Promise period are equivalent to one another for credits attempted, indicating that, from year to year, the incremental increase in credits attempt is not significantly larger. However, Wald tests do reject the null that coefficients are equal for percent credits earned for 2015 v. 2017 for first-generation students, and 2016 v. 2017 for all three samples, indicating that the incremental decrease in percent credits earned is significantly larger over time. Moreover, first-generation students are predicted to earn more credits, but earn lower GPAs, in the first-year following Promise. Differences in years two and three were not significantly different as compared to the pre-Promise period. Estimates from models excluding TPS follow similar patterns, though the magnitude of coefficients is smaller (Table 3-12).

Results in Table 3-11 generally support results from the fully specified models in Table 3-10, Panel A. Both model specifications estimate comparable coefficients for first-generation students in terms of credits attempted and earned, and term GPA following Promise initiation. Estimates from models operationalizing post-Promise changes as three level-change variables diverge from the level- and slope-change specification with respect to percent credits earned. While the latter observe no significant change in percent credits earned for any sample, the former predict negative and significant changes across all three samples. This may be because models in Table 3-10 are able to account for the post-Promise change in slope, which could account for some of the level-changes by year observed in Table 3-11. Overall, results indicate that, following the initiation of the Tennessee Promise, both first-generation and non-first-generation students attempt more credits, and first-generation students in particular earn greater credits, yet earn lower GPAs. This pattern holds even for students who do not complete all Promise requirements.

RQ3: To what extent do differences vary for first-generation students enrolled in community colleges and first-generation students enrolled in four-year colleges?

Following Promise-initiation, students are 25 percent more likely to enroll in a community college, with first-generation enrollment in a community college increasing by 21 percent and non-first-generation enrollment increasing by 28 percent (Figure 3-8). A descriptive look at post-Promise differences outcomes by institution type shows increases in credits attempted and earned in community colleges, as well as a decrease in the first-term GPA (Figure 3-9). Differences in outcomes in four-year colleges are not visually apparent. Results from Chow tests indicate that predictors operate differently across community college and four-year institutions, motivating the use of subgroup analyses to examine outcomes by institution type.

The four subgroup models shown in Table 3-13 estimate changes in outcomes for students based on their first-generation status and their institution of enrollment. Models include institution and major fixed effects within institution type. Results provide evidence that both first-generation and non-first-generation students in community colleges attempt and earn more credits in their first term (attempting about 1.1 more credit and earning about 0.9 more credits), Both first-generation and non-first-generation students enrolling in community colleges also earn GPAs 0.11- 0.13 points lower. No changes on the level-change variable are observed in models estimating percent credits earned for students enrolling in community colleges in either group. Nevertheless, the initiation of the Tennessee Promise is associated with a -1.3 percentage point shift in the slope of the post-Promise trend line for non-first-generation students in community colleges, suggesting that non-first-generation students who enroll in community colleges following Promise may be performing worse than their before.

Overall, Wald tests of coefficient equivalence do not provide evidence that coefficients between first-generation and non-first-generations students within community colleges are significantly different from one another. In terms of changes in outcomes for students enrolling in four-year institutions, non-first-generation students are predicted to attempt 0.12 more credits following Promise initiation. No other changes are observed for students enrolling in four-year institutions following Promise initiation. Figure 3-10 displays the changes for students in community colleges and the relative stability in outcomes for students enrolling in four-year institutions following Promise initiation.

Models excluding TPS provide important nuance to the story (Table 3-14). The sign and significance of coefficients on term credits attempted in community colleges matches the main results, though coefficients are smaller in magnitude. The magnitude of coefficients on the level change for post-Promise credits earned in community college are about half as large, and none are statistically significant. While the coefficient on level-change for non-first-generation students' community college GPA is no longer significantly different from zero, the coefficient is relatively comparable to that estimated in the full sample. However, the coefficient for first-generation students' GPA is negative, significant, and slightly higher in magnitude. The coefficient on level-change with respect to term credits attempted for non-first-generation students enrolled in a four-year is relatively unchanged. This makes sense as few observations are removed from this subgroup.

Overall, findings indicate that first-generation students attempt and earn more credits, yet earn lower GPAs, following the initiation of the Tennessee Promise. These changes appear to be driven by changes at the community college level. Decreases in the magnitude of coefficients upon removal of Tennessee Promise Students suggests that first-generation TPS are more likely to attempt and earn more credits, potentially explaining some of the changes to credits earned post-Promise. However, there remains a post-Promise bump in credits attempted for non-TPS first-generation students, as well a significant decrease in GPA, suggesting that exposure to the TN Promise created changes for first-generation students more broadly.

Robustness and Sensitivity Checks

To try and further isolate the relationship between the initiation of the TN Promise and changes to first-generation students' outcomes, two checks are conducted to address concerns of internal validity, namely, (a) threat of history and (b) varying definitions of first-generation. In the section below, each threat to internal validity and the tests performed are discussed.

Threat of History

A primary threat to internal validity in an ITS analysis in this context is the threat of history which may erroneously ascribe the effect of concurrently occurring programs on students' outcomes to Promise-initiation (Cook & Campbell, 1979). The Tennessee Transfer Pathways (TTP) program was initiated around the time as the TN Promise and may also have had an influence on students' postsecondary achievement. The aim of TTP is to help students transfer from two-year to four-year institutions by easing credit transfer for particular majors. The TTP program was initiated in 2012 in some institutions and was expanded to include more institutions over time. The information students may have received about the program or from TTP participation may have encourage more students to choose TTP majors, which could have affected students' credit and GPA attainment in their first semester.[43]

To address the threat to internal validity from the TTP program, models from the main analysis were re-estimated with the intervention start time artificially changed to the 2012, 2013, and 2014 school years, the three years prior to Tennessee Promise implementation during which TTP was active. Results from models with alternate-intervention years are shown in Table 3-15. A significant coefficient is observed on the level-change variable for two outcome variables if the intervention year was 2012, and for zero outcome variables if the intervention year was 2013 or 2014. Comparatively, when the intervention year is 2015, the model estimates significant coefficients on the level-change variable for three of the four outcomes. Additionally, a statistically significant coefficient is observed on the post-intervention slope change variable for

[43] The number of TTP students in the first cohort of TTP is relatively small; of the 32,296 students in the Fall 2012 cohort enrolling in public, Tennessee institutions able to be identified in the National Student Clearinghouse Data, about 15 percent enrolled in a TTP during a six-year period (Tennessee Higher Education Commission, 2019)

one outcome if the intervention year was 2012, and two outcomes if the intervention year was 2013 or 2014, compared to zero significant variables if the intervention year was 2015.[44]

While there appear to be minor changes in students' post-secondary outcomes in years other than 2015, it should be noted that when estimating results for 2012 and 2013, there are too few years of pre-intervention data to accurately estimate a pre-intervention slope. Hence, these models may incorrectly ascribe trends or fluctuations in the outcome to a significant pre-post difference.[45] Furthermore, models for alternate intervention years yield mostly null results, whereas patterns in the post-Promise period consistently observe significant coefficients on the level-change variable for three out of four outcomes. Hence, this study concludes that the threat of history is likely minor, though not able to be fully ruled out.

Varying Definitions of First-Generation

The way first-generation students are defined varies across policies and studies (D'Amico & Dika, 2013; Ishitani, 2016; Terenzini et al., 1996; Warburton et al., 2001; Whitley et al., 2018). Studies have found that the way the definition is constructed matters, as results may vary when certain students are included or excluded from the intervention sample (Toutkoushian et al., 2019). Thus, a second concern is that findings from the study are a function of the way first-generation students are defined. To address this concern, the models in Table 3-10 were re-estimated using two additional indicators of first-generation status. The first is a binary indicator equal to one when students have no degree-holding parents and zero otherwise. This more conservative definition of first-generation aligns with THEC's definition and holds students who have at least one degree-holding parent as non-first-generation. The second indicator is a

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44 Alternate intervention year models estimated on subgroup samples of first-generation and non-first-generation students showed similar patterns (Appendix Tables A3-6 and Table A3-7).
45 Appendix Table A3-8, which breaks down the mean outcomes by year, shows some fluctuation in the pre-Promise outcomes.

categorical variable that divides first-generation students into two groups: those with no degree-holding parents and those with exactly one degree-holding parent. These students were then compared to non-first-generation students, i.e. those with two degree-holding parents. This indicator examines variation in post-Promise outcomes for students based on level of parental education.

As seen in Table 3-16, Panel A, when defined more conservatively, first-generation students are still predicted to attempt more credits (0.67) yet earn lower GPAs (-.011) following the initiation of Promise. Coefficients are similar in magnitude as those in Table 3-10, which show the estimates using the broader definition of first-generation students, though the estimated post-Promise change in GPA is greater in Table 3-16. Results hold once TPS are removed (Panel B), though estimates are smaller in magnitude for term credits attempted. However, the more conservative definition no longer predicts a significant increase in credits earned for first-generation students. When students with one degree-holding parent are counted as first-generation students, as in Table 3-10, first-generation students are predicted to earn 0.48 more credits following Promise-initiation. When students with one degree-holding parent are counted as non-first-generation students, as in Table 3-16, non-first-generation students are predicted to earn 0.45 more credits following Promise. Once TPS students are removed, the coefficient is not significant for students according to either definition. Results using the more conservative definition of first-generation show that students with no degree-holding parents appear to be driving results for credits attempted and GPA, but students with one degree-holding parent are driving results for credits earned. Figure 3-11 provides an illustration of results in Table 3-16, Panel A.

This finding is further substantiated by results in Table 3-17, which present estimates using the categorical variable for first-generation status. Table 3-17 reveals that, while all students attempt more credits, the estimated change was largest for first-generation students with neither parent holding a degree (0.67) or one parent holding a degree (0.63 credits), as compared to the change in credits attempted for non-first-generation students (0.51). Patterns hold when Tennessee Promise Students are excluded, though the magnitude of coefficients is again smaller (closer to zero). Additionally, first-generation students with one degree-holding parent earn significantly more credits, while students with no degree-holding parents see no such change post-Promise.

Findings from this check for robustness suggest that there are some differences in first-generation students based on their access to parental capital by way of number of degree-holding parents. While students with no degree-holding parents are associated with the largest increase in credits attempted, they are also associated with a significant dip in their GPA. First-generation students with one degree-holding parent—who thereby have some access to parental capital around college-going—are more likely to find success in earning more credits, which may relate to their greater access to information on college from their parents. Altogether, differentiating between definitions of first-generation students yields results that mirror those observed in the main specifications, while also illustrating some expected variation within first-generation students.

Discussion

First-generation students face numerous challenges accessing college and finding success once enrolled. In experiencing barriers such as a lack of financial resources and information on how to navigate the college application process, first-generation students are often comparatively disadvantaged relative to their non-first-generation peers. The profusion of local and statewide "college promise" programs, located in 82 percent of states, makes them an ideal channel through which first-generation students may access funding and other supports to ease their transition to college. The Tennessee Promise is especially well-suited to study the way in which first-generation may have benefitted from exposure to the initiation of the state's program. As the criteria are relatively broad, almost all students in the state are eligible to apply, and thus receive targeted encouragement and supports from schools and/or nonprofit partners. In this way, students across the state receive valuable information and guidance initiated by the TN Promise such as support filing the FAFSA and mentorship.

Even if students did not complete all requirements to be eligible to receive funding, or, did complete all requirements but did not ultimately receive any Promise funding (e.g. if Pell or state aid covered their tuition), students may still have received many benefits from having "Promise-potential". Students with less exposure to the Program may have received information about college opportunities and have engaged no further. Students with greater exposure may have attended workshops, received federal or state funding from filing their FAFSA, or received guidance from their mentor. As first-generation students have a demonstrated need for financial and informational supports, they may benefit greatly from engagement with the TN Promise.

This study used an interrupted time series strategy to examine how the initiation of the Tennessee Promise program is associated with changes in first-generation students' first-term credit and GPA outcomes. This analysis is able to leverage a rich set of data, controlling for students' demographic characteristics, level of academic preparation, access to financial resources, institution of enrollment, and major. The analysis finds that, while both first-generation and non-first-generation students experience increases in credits attempted, first-generation students attempt significantly more credits in their first-term compared to their peers. Moreover, only first-generation students also earn more credits. Patterns generally hold even when Tennessee Promise Students are removed from the sample or when the sample is restricted to community college enrollment. This is noteworthy, as it raises important questions about the relative importance of information, awareness, and support offered by the Promise program to high school seniors in comparison with the promise of financial benefits.

There is no corresponding change in percent credits earned for students in either group, suggesting that, despite gains in credits attempted and earned, first-generation students are not earning proportionally greater credits following the initiation of TN Promise. Although first-generation students attempt and earn more credits, first-generation students enrolling after Promise initiation also have lower GPAs. Unlike with credits attempted and earned, the magnitudes of the coefficients for the post-Promise change in GPA remain unchanged when TPS are removed. Given the change in study composition, this raises the question as to whether students who attempt more credits following Promise—who may be academically less prepared—experience challenges completing the larger course load. Some of the observed changes in outcomes for first-generation students may be explained by the changes in the student composition following the initiation of Promise, after which first-generation students are more likely to be Black or Latinx, and have significant lower ACT scores.

That changes appear to be driven by changes amongst students enrolling in community colleges makes sense, as the primary directive of the Tennessee Promise is to guarantee students tuition-free enrollment at two-year institutions. While funds can be used at select four-year institutions, funds would not fully cover tuition as in two-year colleges, and few students in the sample used this option. The fact that almost no changes were observed amongst students enrolling in four-year universities is thus noteworthy. Despite students receiving information about college access and potentially even greater funding from the Promise program, having access to this information did not appear to shift the first-term outcomes of students in four-year universities, though the change in composition of students enrolling post-Promise may explain these null results. In contrast, students enrolling in community colleges experienced increases in credits attempted and earned without having received funding from the Promise.

The change in composition of students enrolling after the initiation of Tennessee Promise is an important takeaway from this analysis. Starting in 2015, first-generation students who are students of color and those with lower ACT scores are more likely to enrolled than in previous years. The changes are concentrated amongst first-generation students. As a program seeking to improve students' access to higher education attainment, it is beneficial that such a change in the composition of first-generation students is observed, as it indicates an increase in enrollment amongst students who may not previously have enrolled. As evidenced by the predicted increases in credits attempted and earned, there may be a positive relationship between exposure to the Promise and students' first-term credit attainment goals. The change in the composition of students after the introduction of the Promise program limits the ability of this study to draw causal conclusions, and thus, the study reports associations.

Despite attempting and earning a greater number of credits, the overall outcomes for students is not all rosy. Students did not experience a shift in the percent of credits earned of those attempted, and first-generation students continued to trail behind their peers in this regard, earning approximately 76 percent of credits attempted, compared to their peers who earned 80 percent. Furthermore, first-generation students had significantly lower GPAs in the post-Promise period, the magnitude of which stayed consistent even when looking at students who were not

Tennessee Promise Students. While average post-Promise GPA for first-generation students was 0.07 – 0.12 points lower than their pre-Promise GPA, these relatively small differences do matter from a policy perspective. The minimum GPA required for students to achieve an associate's degree is 2.0, and earning a GPA between 1.0 – 2.0 (depending on the number of cumulative credit hours earned) may place a student on academic probation for a semester (Tennessee Board of Regents, 2020).[46] Thus, for some students on the margins, even a tenth of a point difference could affect their academic standing.

Conclusion

First-generation students typically do not have parents with firsthand experience navigating the college application and completion process and may have incomplete information to weigh the benefits and costs of college options (Perna, 2006, 2015; Perna & Riepe, 2016). Simply having informational access is not enough; first-generation students benefit most when they have a mentor or counselor to guide them through the many steps required for college attendance (Bettinger et al., 2012; Tierney et al., 2009; Perna, 2010; Perna & Riepe, 2016). They also do not have sufficient access to this information from school guidance counselors, who, on average, spend only about one third of their time on postsecondary admissions counseling divided across a caseload of an average of 400 students (Clinedinst et al., 2013).

[46] For instance, while there is no minimum required GPA for students earning under 14 cumulative credits, students must maintain at least a 1.0 GPA when completing credits 14-26. In the sample in the post-Promise period, about 3,400 students earn GPAs between 0.8 and 1.2 in their first term, i.e., within 0.2 points above and below the minimum required GPA for their second term. This comprises 5 percent of the students in the sample. That means that about 5 percent of the students must make significant gains to bring up or maintain their first-term GPA to meet the minimum requirement of 1.0 in their second term. Of the students on the margin, 75 percent are first-generation students. Given that first-generation students are predicted to earn lower GPAs in the post-Promise period, they are disproportionately at greater risk of being placed on academic probation.

The Tennessee Promise's guarantee of a tuition-free college enrollment created a bounty of resources and statewide shifts for students. The shift in the narrative for students from a possibility of receiving a scholarship to a guarantee of receiving funding is a powerful motivator to complete the additional steps and benchmarks the Promise asks of its applicants. In this way, the Tennessee Promise creates a straightforward and clear pathway for students to access higher education, which is all the more important for first-generation students. Of recommendations from scholars such as Perna (2015) and Tierney and colleagues (2009) to improve college access and success, three are addressed by promise programs: "1) target students with the greatest financial need; 2) assist students with navigating pathways into and through college, with particular attention to financial aid processes;…[and] 3) adapt services to recognize the relevant context and characteristics of targeted students" (Perna, 2015, p. 4). Promise programs are both widely available and contextually-responsive, and hence able to provide high-needs students with funding essential to their college access (Perna, 2015). As Perna (2006) describes in her conceptual model for examining college access, college access and success is determined by a multitude of intertwined factors, including cultural capital, local community support, resources from higher education institutions, and the larger policy context. In improving students' access to information on college, financial resources, shifting the expectations around college going, and creating a state-wide conversation around college going, the Tennessee Promise is able to create a change in all four of the domain's in Perna's (2006) framework. For first-generation students, who particularly are in need of financial and informational resources, programs like the Tennessee Promise may offer much needed support. Existing promise programs may consider reflecting on how their own programs facilitate these resources through targeted programming for first-generation students.

This study finds that first-generation students who were exposed to a statewide tuition and mentoring program affords students benefits beyond just additional funding. First-generation students who may not have previously considered college in the past are enrolling and are attempting and earning more credits than before. However, given that these students are also academically less prepared and less resourced than their non-first-generation peers, it is vital that universities and policymakers consider offering students additional supports to help students succeed after the transition. Potential supports may include peer and faculty networks, tutoring services, and academic guidance, which may be offered independently, or as wraparound services through programs like Nashville GRAD and Knox Promise (Adelman, 1993; Dennis et al., 2005; Ishitani, 2006; Orbe, 2004; Stephens et al., 2012).[47] Understanding how this statewide program supports first-generation students will inform stakeholders' ongoing efforts to support and expand access to postsecondary education for students in traditionally underserved populations.

Future work may consider studies that are able to parse out variation in the types of supports provided by Promise program, such as informational, financial, and mentoring, and the extent to which supports help facilitate capital and resources for students to better access postsecondary education. Scholars may also examine the ways in which exposure to a Promise program shifts students' medium-term outcomes, such as vertical transfer, or long-term outcomes, such as degree attainment and labor market outcomes. Finally, researchers and policymakers alike should consider scaling best practices from promise programs found to support students from historically marginalized groups.

[47] For more information on these programs, visit: Nashville GRAD and Knox Promise.

References

Abadie, A., Athey, S., Imbens, G., & Wooldridge, J. (2017). *When Should You Adjust Standard Errors for Clustering?* (No. w24003; p. w24003). National Bureau of Economic Research. https://doi.org/10.3386/w24003

Adelman, C. (1993). Insult, But No Injury: You Are Now a First-Generation College Student. *Educational Record; Washington*, *74*(1), 53.

Andrews, R. J., DesJardins, S., & Ranchhod, V. (2010). The effects of the Kalamazoo Promise on college choice. *Economics of Education Review*, *29*(5), 722–737. https://doi.org/10.1016/j.econedurev.2010.05.004

Atherton, M. C. (2014). Academic Preparedness of First-Generation College Students: Different Perspectives. *Journal of College Student Development; Baltimore*, *55*(8), 824–829.

Barry, L. M., Hudley, C., Kelly, M., & Cho, S.-J. (2009). Differences in self-reported disclosure of college experiences by first-generation college student status. *Adolescence*, *44*(173), 55.

Bartik, T. J., Hershbein, B., & Lachowska, M. (2017). *The effects of the Kalamazoo Promise scholarship on college enrollment, persistence, and completion* (Working Paper No. 15-229; pp. 1–65). Upjohn Institute. https://research.upjohn.org/up_workingpapers/229/

Bean, J. P. (1983). The Application of a Model of Turnover in Work Organizations to the Student Attrition Process. *The Review of Higher Education*, *6*(2), 129–148. https://doi.org/10.1353/rhe.1983.0026

Berger, J. (2000). Optimizing capital, social reproduction, and undergraduate persistence. In J. M. Braxton (Ed.), *Reworking the student departure puzzle* (pp. 195–224). Vanderbilt University Press.

Bettinger, E. P., Long, B. T., Oreopoulos, P., & Sanbonmatsu, L. (2012). The Role of Application Assistance and Information in College Decisions: Results from the H&R Block Fafsa Experiment. *The Quarterly Journal of Economics*, *127*(3), 1205–1242. https://doi.org/10.1093/qje/qjs017

Bills, D. B. (2003). Credentials, Signals, and Screens: Explaining the Relationship between Schooling and Job Assignment. *Review of Educational Research*, *73*(4), 441–469. JSTOR.

Bourdieu, P. (1977). Cultural reproduction and social reproduction. In J. Karabel & A. H. Halsey (Eds.), *Power and Ideology in Education* (pp. 487–511). Oxford University Press.

Bourdieu, P. (1986). The Forms of Capital. In A. Sadovnik (Ed.), *Sociology of Education: A Critical Reader* (2nd ed., pp. 83–95). Routledge Taylor & Francis Group.

Bozick, R., Gonzalez, G., & Engberg, J. (2015). *Using a Merit-Based Scholarship Program to Increase Rates of College Enrollment in an Urban School District: The Case of the Pittsburgh Promise*. *45*, 25.

Bruce, D. J., & Carruthers, C. K. (2014). Jackpot? The impact of lottery scholarships on enrollment in Tennessee. *Journal of Urban Economics*, *81*, 30–44. https://doi.org/10.1016/j.jue.2014.01.006

Bui, K. V. T. (2002). First-generation college students at a four-year university: Background characteristics, reasons for pursuing higher education, and first-year experiences. *College Student Journal*, *36*(1), 3–11.

Calahan, M., Perna, L. W., Yamashita, M., Wright, J., & Santillan, S. (2018). *2018 Indicators of Higher Education Equity in the United States: Historical Trend Report* (pp. 1–152). The Pell Institute for the Study of Opportunity in Higher Education, Council for Opportunity in Education (COE), and Alliance for Higher Education and Democracy of the University of Pennsylvania (PennAHEAD). http://pellinstitute.org/downloads/publications-Indicators_of_Higher_Education_Equity_in_the_US_2018_Historical_Trend_Report.pdf

Cameron, C. A., & Miller, D. L. (2015). A Practitioner's Guide to Cluster-Robust Inference. *Journal of Human Resources*, *50*(2), 317–372. https://doi.org/10.3368/jhr.50.2.317

Carruthers, C. K., & Fox, W. F. (2016). Aid for all: College coaching, financial aid, and post-secondary persistence in Tennessee. *Economics of Education Review*, *51*, 97–112. https://doi.org/10.1016/j.econedurev.2015.06.001

Cataldi, E. F. (2018). *First-Generation Students: College Access, Persistence, and Postbachelor's Outcomes*. 31.

Choy, S. (2001). Students whose parents did not go to college: Postsecondary access, persistence, and attainment. In *National Center for Education Statistics, The condition of education.* (pp. xviii–xliii).

Choy, S. (2002). *Students Whose Parents Did Not Go to College: Postsecondary Access, Persistence, and Attainment: (492182006-021)* [Data set]. American Psychological Association. https://doi.org/10.1037/e492182006-021

Clinedinst, M. E., Hurley, S. F., & Hawkins, D. A. (2013). *State of college admission 2013*. National Association for College Admission Counselors.

Coleman, J. S. (1988). Social Capital in the Creation of Human Capital. In A. R. Sadovnik (Ed.), *Sociology of Education: A Critical Reader* (2nd ed., pp. 97–113). Routledge.

Cook, T. D., & Campbell, D. T. (1979). *Quasi-experimentation: Design and Analysis Issues for Field Settings.* Rand McNally.

D'Amico, M. M., & Dika, S. L. (2013). Using Data Known at the Time of Admission to Predict First-Generation College Student Success. *Journal of College Student Retention: Research, Theory & Practice*, *15*(2), 173–192. https://doi.org/10.2190/CS.15.2.c

Daugherty, L., & Gonzalez, G. (2016). *The Impact of the New Haven Promise Program on College Enrollment, Choice, and Persistence*. RAND Corporation. https://doi.org/10.7249/WR1147

Dennis, J. M., Phinney, J. S., & Chuateco, L. I. (2005). The Role of Motivation, Parental Support, and Peer Support in the Academic Success of Ethnic Minority First-Generation College Students. *Journal of College Student Development*, *46*(3), 223–236. https://doi.org/10.1353/csd.2005.0023

Doyle, W. R. (2010). Changes in Institutional Aid, 1992–2003: The Evolving Role of Merit Aid. *Research in Higher Education*, *51*(8), 789–810. https://doi.org/10.1007/s11162-010-9177-0

Engle, J. (2007). Postsecondary access and success for first-generation college students. *American Academic*, *3*(1), 25–48.

Field, J. (2016). *Social Capital* (3 edition). Routledge.

Gonzalez, G., Bozick, R., Daugherty, L., Scherer, E., Singh, R., Jacobo Suárez, M., & Ryan, S. (2014). *Transforming an urban school system: Progress of New Haven School Change and New Haven Promise education reforms (2010-2013)*. RAND Corporation.

Gonzalez, G. C., Bozick, R., Tharp-Taylor, S., & Phillips, A. (2011). *Fulfilling the Pittsburgh promise: Early progress of Pittsburgh's postsecondary scholarship program*. RAND Corporation.

Gurantz, O. (2020). What Does Free Community College Buy? Early Impacts from the Oregon Promise. *Journal of Policy Analysis and Management*, *39*(1), 11–35. https://doi.org/10.1002/pam.22157

Hossler, D., Braxton, J., & Coopersmith, G. (1989). Understanding student college choice. In J. Smart (Ed.), *Higher Education: Handbook of Theory and Research: Vol. V* (pp. 231–288). Agathon Press.

Inman, W. E., & Mayes, L. (1999). The importance of being first: Unique characteristics of first generation community college students. *Community College Review; Raleigh*, *26*(4), 3.

Iriti, J., Page, L. C., & Bickel, W. E. (2018). Place-based scholarships: Catalysts for systems reform to improve postsecondary attainment. *International Journal of Educational Development*, *58*, 137–148. https://doi.org/10.1016/j.ijedudev.2017.02.002

Ishitani, T. (2006). Studying Attrition and Degree Completion Behavior among First-Generation College Students in the United States. *The Journal of Higher Education*, *77*(5), 861–885. https://doi.org/10.1080/00221546.2006.11778947

Ishitani, T. (2016). First-Generation Students Persistence at Four-Year Institutions. *College and University*, *91*(3), 22–33.

Jæger, M. M., & Karlson, K. (2018). Cultural capital and educational inequality: A counterfactual analysis. *Sociological Science*, *5*, 775–795. https://doi.org/10.15195/V5.A33

Johnson, I. (2008). Enrollment, Persistence and Graduation of In-State Students at a Public Research University: Does High School Matter? *Research in Higher Education*, *49*(8), 776–793. https://doi.org/10.1007/s11162-008-9105-8

Kramer, J. W. (2020). Experimental Evidence on the Effects (or Lack Thereof) of Informational Framing During the College Transition. *AERA Open*, *6*(1), 2332858420908536. https://doi.org/10.1177/2332858420908536

Krause, M. (2018, September 25). Tennessee Promise has brought significant positive change. *Inside Higher Ed*. https://www.insidehighered.com/views/2018/09/25/tennessee-promise-has-brought-significant-positive-change-opinion

Lee, J. J., Sax, L. J., Kim, A. K., & Hagedorn, L. S. (2004). Understanding students' parental education beyond first-generation status. *Community College Review*, *32*, 1–20.

Lin, N. (2002). *Social Capital: A Theory of Social Structure and Action*. Cambridge University Press.

Long, K. (2018, June 4). Can 'Tennessee Promise' of free tuition offer lessons for Seattle and Washington? *The Seattle Times*. https://www.seattletimes.com/education-lab/can-tennessee-promise-of-free-tuition-offer-lessons-for-seattle-and-washington/

Martinez, J. A., Sher, K. J., Krull, J. L., & Wood, P. K. (2009). Blue-Collar Scholars?: Mediators and Moderators of University Attrition in First-Generation College Students. *Journal of College Student Development*, *50*(1), 87–103. https://doi.org/10.1353/csd.0.0053

McCarron, G. P., & Inkelas, K. K. (2006). The Gap between Educational Aspirations and Attainment for First-Generation College Students and the Role of Parental Involvement. *Journal of College Student Development*, *47*(5), 534–549. https://doi.org/10.1353/csd.2006.0059

Moffitt, R. (1991). Program Evaluation with Nonexperimental Data. *Evaluation Review*, *15*(3), 291–314.

Møllegaard, S., & Jæger, M. M. (2015). The effect of grandparents' economic, cultural, and social capital on grandchildren's educational success. *Research in Social Stratification and Mobility*, *42*, 11–19. https://doi.org/10.1016/j.rssm.2015.06.004

Moschetti, R. V., & Hudley, C. (2015). Social Capital and Academic Motivation Among First-Generation Community College Students. *Community College Journal of Research and Practice*, *39*(3), 235–251. https://doi.org/10.1080/10668926.2013.819304

Orbe, M. P. (2004). Negotiating multiple identities within multiple frames: An analysis of first-generation college students. *Communication Education*, *53*(2), 131–149. https://doi.org/10.1080/03634520410001682401

Page, L. C., & Iriti, J. E. (2016). On Undermatch and College Cost. In A. P. Kelly, J. S. Howell, & C. Sattin-Bajaj (Eds.), *Matchings Students to Opportunity*. Harvard Education Press.

Page, L. C., Iriti, J. E., Lowry, D. J., & Anthony, A. M. (2018). The Promise of Place-Based Investment in Postsecondary Access and Success: Investigating the Impact of the Pittsburgh Promise. *Education Finance and Policy*, 1–60. https://doi.org/10.1162/edfp_a_00257

Page, L. C., & Scott-Clayton, J. (2016). Improving college access in the United States: Barriers and policy responses. *Economics of Education Review*, *51*, 4–22. https://doi.org/10.1016/j.econedurev.2016.02.009

Palbusa, J. A., & Gauvain, M. (2017). Parent–Student Communication About College and Freshman Grades in First-Generation and Non–First-Generation Students. *Journal of College Student Development*, *58*(1), 107–112. https://doi.org/10.1353/csd.2017.0007

Pascarella, E. T., Pierson, C. T., Wolniak, G. C., & Terenzini, P. T. (2004). First-Generation College Students: Additional Evidence on College Experiences and Outcomes. *The Journal of Higher Education*, *75*(3), 249–284. JSTOR.

Paulsen, M. (1990). *College Choice: Understanding Student Enrollment Behavior.* (ASHE-ERIC Higher Education Report No. 6). George Washington University, School of Education and Human Development.

Perna, L. W. (2006). Studying College Access and Choice: A Proposed Conceptual Model. In J. C. Smart (Ed.), *Higher Education: Handbook of Theory and Research* (Vol. 21, pp. 99–157). Springer. https://doi.org/10.1007/1-4020-4512-3_3

Perna, L. W. (2010). Toward a more complete understanding of the role of financial aid in promoting college enrollment: The importance of context. In J. C. Smart (Ed.), *Higher education: Handbook of theory and research: Vol. XXV* (pp. 129–180). Springer.

Perna, L. W. (2015). Improving College Access and Completion for Low-Income and First-Generation Students: The Role of College Access and Success Programs. *University of Pennsylvania Scholarly Commons*, 14.

Perna, L. W., & Leigh, E. W. (2020). *Database of college promise programs*. University of Pennsylvania, Alliance for Higher Education and Democracy. Retrieved from http://ahead-penn.org/creating-knowledge/college-promise.

Perna, L. W., Leigh, E. W., & Carroll, S. (2017). “Free College:” A New and Improved State Approach to Increasing Educational Attainment? *American Behavioral Scientist*, *61*(14), 1740–1756. https://doi.org/10.1177/0002764217744821

Perna, L. W., & Riepe, J. (2016). *Delivering On the Promise: Structuring College Promise Programs to Promote Higher Education Attainment for Students from Underserved Groups* (p. 9). College Promise Campaign and PennAHEAD.

Schwartz, S. E. O., Kanchewa, S. S., Rhodes, J. E., Gowdy, G., Stark, A. M., Horn, J. P., Parnes, M., & Spencer, R. (2017). "I'm Having a Little Struggle With This, Can You Help Me Out?": Examining Impacts and Processes of a Social Capital Intervention for First-Generation College Students. *American Journal of Community Psychology*, n/a-n/a. https://doi.org/10.1002/ajcp.12206

Stephens, N. M., Fryberg, S. A., Markus, H. R., Johnson, C. S., & Covarrubias, R. (2012). Unseen disadvantage: How American universities' focus on independence undermines the academic performance of first-generation college students. *Journal of Personality and Social Psychology: Interpersonal Relations and Group Processes*, *102*(6), 1178–1197. http://dx.doi.org/10.1037/a0027143

Swanson, E., & Ritter, G. (2018). *Start to Finish: Examining the Impact of the El Dorado Promise on Postsecondary Outcomes* (SSRN Scholarly Paper ID 3153153). Social Science Research Network. https://papers.ssrn.com/abstract=3153153

Swanson, E., Watson, A., Ritter, G. W., & Nichols, M. (2016). Promises Fulfilled? A Systematic Review of the Impacts of Promise Programs. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2849194

Tan, C. Y. (2017). Conceptual diversity, moderators, and theoretical issues in quantitative studies of cultural capital theory. *Educational Review*, *69*(5), 600–619. https://doi.org/10.1080/00131911.2017.1288085

Tennessee Board of Regents. (2020, March). *GPA Community Colleges* [Government]. Undergraduate Academic Retention & GPA Standards. https://policies.tbr.edu/policies/undergraduate-academic-retention-standards

Tennessee Higher Education Commission. (2017). *Tennessee Promise Annual Report* (pp. 1–18). https://www.tn.gov/content/dam/tn/thec/bureau/research/promise/TN%20Promise%20Report%202018%20Final.pdf

Tennessee Higher Education Commission. (2018). *Tennessee Promise Annual Report* (pp. 1–28). https://www.tn.gov/content/dam/tn/thec/bureau/research/promise/TN%20Promise%20Report%202018%20Final.pdf

Tennessee Higher Education Commission. (2019a). *Articulation and Transfer in Tennessee Higher Education* (pp. 1–25).

Tennessee Higher Education Commission. (2019b). *Tennessee Promise Annual Report* (pp. 1–32). https://www.tn.gov/thec/research/redirect-research/tn-promise-annual-report/tn-promise-annual-report.html

Terenzini, P. T., Springer, L., Yaeger, P. M., Pascarella, E. T., & Nora, A. (1996). First-generation college students: Characteristics, experiences, and cognitive development. *Research in Higher Education*, *37*(1), 1–22.

Tierney, W. G., Bailey, T., Constantine, J., Finkelstein, N., & Hurd, N. F. (2009). *Helping students navigate the path to college: What high schools can do: A practice guide* (NCES #2009-4066). National Center for Education Evaluation and Regional Assistance, Institute of Education Sciences, U. S. Department of Education. Retrieved from http://ies.ed.gov/ncee/wwc/ PracticeGuide.aspx?sid=11

Tinto, V. (1993). *Leaving College: Rethinking the Causes and Cures of Student Attrition* (2nd edition). University of Chicago Press.

TN Promise Handbook 2017-2018 (pp. 1–36). (2018). Tennessee Higher Education Commission. http://www.tnpromise.gov/files/TNPromiseHandbook_2017-2018.pdf

Tobolowsky, B. F., Cox, B. E., & Chunoo, V. S. (2017). Bridging the Cultural Gap: Relationships Between Programmatic Offerings and First-Generation Student Benchmarks. *Journal of College Student Retention: Research, Theory & Practice*, *0*(0), 1–25. https://doi.org/10.1177/1521025117742377

Toutkoushian, R. K., May-Trifiletti, J. A., & Clayton, A. B. (2019). From "First in Family" to "First to Finish": Does College Graduation Vary by How First-Generation College Status Is Defined? *Educational Policy*, 089590481882375. https://doi.org/10.1177/0895904818823753

Trostel, P. (2015). *It's Not Just the Money: The Benefits of College Education to Individuals and to Society* (Lumina Issues Papers, pp. 1–73). Lumina Foundation for Education, Margaret Chase Smith Policy Center & School of Economics.

Volunteer to Mentor—Tennessee Promise. (2019). http://www.tnpromise.gov/volunteers.shtml

Warburton, E. C., Bugarin, R., & Nuñez, A.-M. (2001). *Bridging the Gap: Academic Preparation and Postsecondary Success of First-Generation Students* (NCES 2001-153; Postsecondary Education Descriptive Analysis Reports, p. 83). U.S. Department of Education Office of Educational Research and Improvement.

Wardrip, K., Divringi, E., & DeMaria, K. (2018). *How Does Last-Dollar Financial Aid Affect First-Year Student Outcomes?* (p. 28). Federal Reserve Bank of Philadelphia.

Whitley, S. E., Benson, G., & Wesaw, A. (2018). First-generation student success: A landscape of analysis of programs and services at four-year institutions. *NASPA—Student Affairs Administrators in Higher Education*, 84.

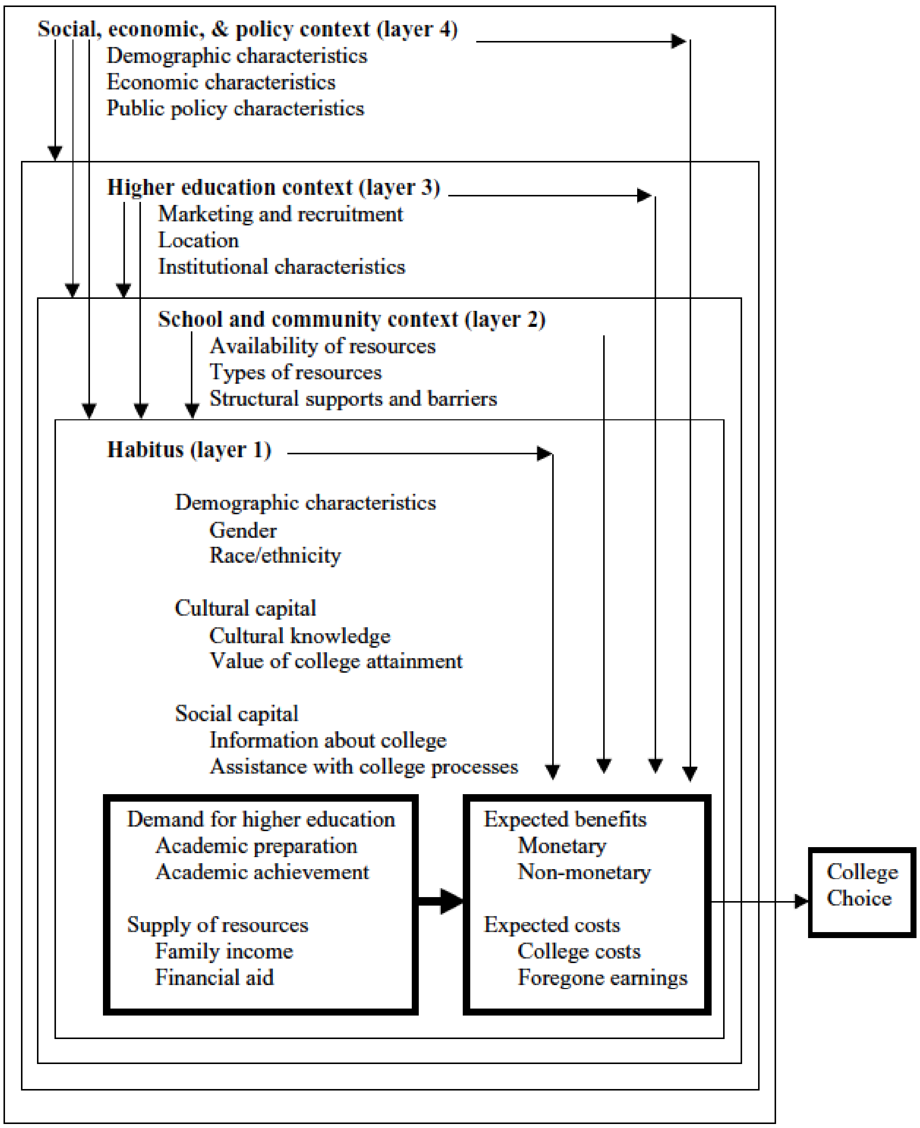
Wilbur, T. G., & Roscigno, V. J. (2016). First-generation Disadvantage and College Enrollment/Completion. *Socius*, *2*, 2378023116664351. https://doi.org/10.1177/2378023116664351

Wildhagen, T. (2015). "Not Your Typical Student": The Social Construction of the "First-Generation" College Student. *Qualitative Sociology*, *38*(3), 285–303. https://doi.org/10.1007/s11133-015-9308-1

Wooldridge, J. M. (2012). *Introductory Econometrics: A Modern Approach* (5th Edition). Cengage Learning.

Tables and Figures

Figure 3- 1 Proposed Conceptual Model of Student College Choice (Perna, 2006)



Notes: Adopted from Perna (2006).

Table 3- 1 Chow Tests of Coefficient Equivalence (First-Generation)

	Partially Interacted 1	Partially Interacted 2	Fully Interacted
Term Attempted	2.91	2.80	1078.36
	(0.05)	(0.03)	(0.00)
Term Earned	3.45	7.23	50.71
	(0.03)	(0.00)	(0.00)
Term GPA	3.19	18.01	500.13
	(0.03)	(0.00)	(0.00)
Percent Term Credits Earned	1.83	8.47	382.46
	(0.16)	(0.00)	(0.00)
Variables Interacted	Level Change, Pre-Trend, and Slope Change	Level Change, Pre-Trend, Slope Change, Parental AGI, Parental EFC, ACT, Dual Enrollment	All Variables

Note: Table displays F-statistics from Chow tests of coefficient equivalence in subgroup models by first-generation status. The values in parentheses display the corresponding p-values of the probability of obtaining an F-statistic at least as high as the one as observed. * p<0.05 **p<0.01 ***p<0.001

Table 3- 2 Chow Tests of Coefficient Equivalence (Institution Type)

	Partially Interacted 1	Partially Interacted 2	Fully Interacted
Term Attempted	7.89	20.50	388.68
	(0.00)	(0.00)	(0.00)
Term Earned	14.91	14.14	2300.14
	(0.00)	(0.00)	(0.00)
Term GPA	47.56	66.15	117231.19
	(0.00)	(0.00)	(0.00)
Percent Term Credits Earned	23.50	16.54	788.64
	(0.00)	(0.00)	(0.00)
Variables Interacted	Level Change, Pre-Trend, and Slope Change	Level Change, Pre-Trend, Slope Change, Parental AGI, Parental EFC, ACT, Dual Enrollment	All Variables

Note: Table displays F-statistics from Chow tests of coefficient equivalence in subgroup models by institution type. The values in parentheses display the corresponding p-values of the probability of obtaining an F-statistic at least as high as the one as observed. * p<0.05 **p<0.01 ***p<0.001

Table 3- 3 Descriptive Statistics of Predictors in the Full Sample, Pre- and Post-Promise

	Means		T-Test		Overall Characteristics		
	Pre-Promise	Post-Promise	Difference	P-Value	Sample Average	Min	Max
Demographic Characteristics							
Male	44.68%	44.06%	-0.62	0.01	44.44%	0%	100%
Female	55.32%	55.94%	0.62	0.01	55.56%	0%	100%
White	70.33%	68.56%	-1.77	0.00	69.64%	0%	100%
Black	19.25%	19.12%	-0.12	0.51	19.20%	0%	100%
Latinx	2.93%	4.42%	1.49	0.00	3.51%	0%	100%
Asian	1.51%	1.66%	0.15	0.01	1.57%	0%	100%
Other	5.98%	6.24%	0.26	0.02	6.08%	0%	100%
First-Gen	62.40%	68.62%	6.22	0.00	64.84%	0%	100%
Neither Parent College	35.89%	36.39%	0.50	0.03	36.09%	0%	100%
One Parent College	26.50%	32.23%	5.72	0.00	28.75%	0%	100%
Both Parents College	37.60%	31.38%	-6.22	0.00	35.16%	0%	100%
Academic Preparedness							
ACT Composite	20.81	20.52	-0.28	0.00	20.70	1	36
ACT Composite (Bottom 25%)	29.87%	32.80%	0.03	0.00	31.02%	0%	100%
ACT Composite (25-50%]	29.20%	28.97%	0.00	0.28	29.11%	0%	100%
ACT Composite (50-75%]	22.85%	21.94%	-0.01	0.00	22.49%	0%	100%
ACT Composite (Top 25%)	18.07%	16.29%	-0.02	0.00	17.37%	0%	100%
Never Dual Enrolled in H.S.	85.27%	92.95%	7.68	0.00	88.29%	0%	100%
Dual Enrolled in H.S.	14.73%	7.05%	-7.68	0.00	11.71%	0%	100%
First Enrolled at Age 17	0.91%	0.73%	-0.18	0.00	0.84%	0%	100%
First Enrolled at Age 18	45.13%	45.19%	0.07	0.78	45.15%	0%	100%
First Enrolled at Age 19-24	53.97%	54.08%	0.11	0.64	54.01%	0%	100%

Financial Resources							
Student AGI	$2,224	$2,080	- $143	0.22	$2,167	$ 1	$8,500,000+
Parent AGI	$68,984	$74,800	$5,816	0.00	$71,272	$1	$8,100,000+
Parental EFC	$15,775	$18,544	$2,768	0.00	$16,864	$1	$3,700,000+
Parental EFC < $6,000	52.72%	52.07%	-0.65	0.01	52.47%	0%	100%
Parental EFC $6,000-21,000	25.62%	24.57%	-1.04	0.00	25.21%	0%	100%
Parental EFC $21,000-75,000	17.67%	18.53%	0.86	0.00	18.01%	0%	100%
Parental EFC $75,000 +	3.99%	4.82%	0.83	0.00	4.32%	0%	100%
Pell Eligible	52.85%	52.36%	-0.49	0.04	52.66%	0%	100%
TSAA Grant Eligible	22.05%	38.01%	15.95	0.00	28.33%	0%	100%
HOPE Access Eligible	1.17%	1.02%	-0.16	0.00	1.11%	0%	100%
HOPE Aspire Eligible	21.80%	20.27%	-1.53	0.00	21.20%	0%	100%
HOPE GAM Eligible	2.63%	2.41%	-0.22	0.00	2.54%	0%	100%
HOPE Eligible	46.61%	45.06%	-1.55	0.00	46.00%	0%	100%
Institutional							
Community College	41.83%	54.33%	12.51	0.00	46.75%	0%	100%
Four-Year College	58.17%	45.67%	-12.51	0.00	53.25%	0%	100%
Unknown/General Major	47.38%	51.29%	3.91	0.00	48.92%	0%	100%
Arts/Humanities Major	7.05%	6.32%	-0.73	0.00	6.77%	0%	100%
Business Major	6.96%	7.36%	0.40	0.00	7.12%	0%	100%
Health/Medicine Major	15.79%	14.53%	-1.26	0.00	15.29%	0%	100%
STEM Major	12.29%	10.75%	-1.55	0.00	11.69%	0%	100%
Social Sciences Major	8.06%	6.77%	-1.29	0.00	7.56%	0%	100%
Trade Major	2.45%	2.98%	0.52	0.00	2.66%	0%	100%
N Observations	113,520	73,597			187,117		

Note: Table shows first-term differences in means for cohorts entering pre- and post-Promise initiation across all predictors in the main analytic sample. Pre-Promise cohorts include those entering between the 2010/11 through 2014/15 school years. Post-Promise cohorts include those entering between the 2015/16 through 2017/18 school years. Column 3 shows the difference in pre- and post-Promise means for each covariate. Differences shown as percentage points, dollars, or ACT points, depending on the unit for the covariate. Column 4 shows the p-value from two-sided t-tests of mean equivalence. * p<0.05 **p<0.01 ***p<0.001

Table 3- 4 Descriptive Statistics of Outcomes in the Full Sample, Pre- and Post-Promise

	Means		T-Test		Overall Characteristics		
	Pre-Promise	Post-Promise	Difference	P-Value	Sample Average	Min	Max
First-Term Outcomes							
Credits Attempted	13.58	14.18	0.60	0	13.82	1	22
Credits Earned	11.48	11.93	0.45	0	11.66	0	22
Percent Credits	84.19%	83.99%	-0.20	0.092	84.11%	0%	100%
GPA	2.61	2.58	-0.03	0	2.60	0	4
N Observations	113,520	73,597			187,117		

Note: Table shows first-term differences in means for cohorts entering pre- and post-Promise initiation across all outcomes in the main analytic sample. Pre-Promise cohorts include those entering between the 2010/11 through 2014/15 school years. Post-Promise cohorts include those entering between the 2015/16 through 2017/18 school years. Column 3 shows the difference in pre- and post-Promise means for each covariate. Differences shown as number of credits, percentage points, or GPA points, depending on the unit for the covariate. Column 4 shows the p-value from two-sided t-tests of mean equivalence.
* p<0.05 **p<0.01 ***p<0.001.

Table 3- 5 Descriptive Statistics of Predictors, Pre- and Post-Promise, by First-Generation Status

	Panel A: First-Generation				Panel B: Non-First-Generation			
	Pre-Promise	Post-Promise	Difference	P-Value	Pre-Promise	Post-Promise	Difference	P-Value
Demographic Characteristics								
Male	43.24%	41.66%	-0.02	0	47.07%	49.31%	0.02	0
Female	56.76%	58.34%	0.02	0	52.93%	50.69%	-0.02	0
White	69.12%	65.40%	-0.04	0	72.35%	75.47%	0.03	0
Black	19.87%	21.42%	0.02	0	18.20%	14.10%	-0.04	0
Latinx	3.44%	5.24%	0.02	0	2.09%	2.62%	0.01	0
Asian	1.58%	1.54%	0.00	0.538	1.40%	1.93%	0.01	0
Other	5.99%	6.41%	0.00	0.003	5.96%	5.88%	0.00	0.687
Academic Preparedness								
ACT Composite	20.17	19.92	-0.25	0	21.87	21.85	-0.01	0.708
ACT Composite (Bottom 25%)	34.78%	37.97%	0.03	0	21.73%	21.50%	0.00	0.499
ACT Composite (25-50%]	30.47%	29.75%	-0.01	0.006	27.10%	27.28%	0.00	0.622
ACT Composite (50-75%]	21.30%	20.14%	-0.01	0	25.42%	25.88%	0.00	0.199
ACT Composite (Top 25%)	13.45%	12.15%	-0.01	0	25.75%	25.34%	0.00	0.251
Never Dual Enrolled	88.61%	94.65%	0.06	0	79.73%	89.23%	0.09	0
Dual Enrolled	11.39%	5.35%	-0.06	0	20.27%	10.77%	-0.09	0
Financial Resources								
Student AGI	$2,054	$1,917	- $137	0.023	$2,507	$2,438	- $68	0.831
Parent AGI	$52,366	$56,425	$4,059	0	$96,562	$114,981	$18,419	0
Parent EFC	$9,437	$10,723	$1,286	0	$26,293	$35,644	$9,351	0
Parental EFC < $6,000	62.57%	62.40%	0.00	0.549	36.37%	29.48%	-0.07	0
Parental EFC $6,000-21,000	24.64%	23.66%	-0.01	0	27.24%	26.56%	-0.01	0.061
Parental EFC $21,000-75,000	11.34%	12.07%	0.01	0	28.17%	32.66%	0.04	0
Parental EFC $75,000 +	1.44%	1.86%	0.00	0	8.22%	11.30%	0.03	0

Pell Eligible	62.34%	62.39%	0.00	0.858	37.11%	30.43%	-0.07	0
TSAA Grant Eligible	27.16%	46.54%	0.19	0	13.58%	19.35%	0.06	0
HOPE Access Eligible	1.43%	1.27%	0.00	0.017	0.75%	0.47%	0.00	0
HOPE Aspire Eligible	26.22%	24.69%	-0.02	0	14.47%	10.61%	-0.04	0
HOPE GAM Eligible	1.27%	1.30%	0.00	0.652	4.88%	4.82%	0.00	0.747
HOPE Eligible	39.50%	37.97%	-0.02	0	58.42%	60.58%	0.02	0
Institutional								
Community College	48.02%	59.17%	0.11	0	31.55%	43.75%	0.12	0
Four-Year College	51.98%	40.83%	-0.11	0	68.45%	56.25%	-0.12	0
Unknown/General Major	47.67%	52.39%	0.05	0	46.90%	48.89%	0.02	0
Arts/Humanities Major	7.05%	6.36%	-0.01	0	7.05%	6.23%	-0.01	0
Business Major	6.48%	6.67%	0.00	0.186	7.77%	8.87%	0.01	0
Health/Medicine Major	17.58%	15.57%	-0.02	0	12.82%	12.25%	-0.01	0.037
STEM Major	10.76%	9.44%	-0.01	0	14.84%	13.61%	-0.01	0
Social Sciences Major	7.79%	6.43%	-0.01	0	8.53%	7.51%	-0.01	0
Trade Major	2.67%	3.13%	0.00	0	2.10%	2.64%	0.01	0
N Observations	70,835	50,501			42,685	23,096		

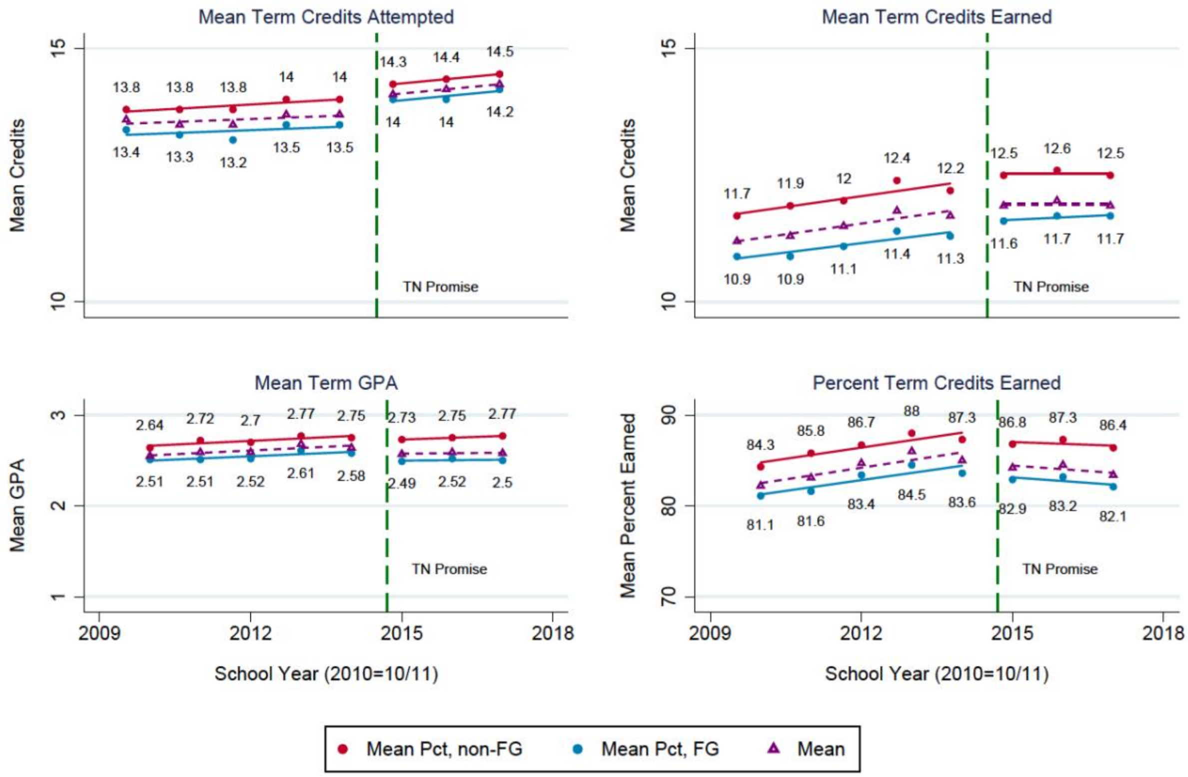
Note: Table shows first-term difference in means for first-generation (Panel A) and non-first-generation students (Panel B), pre- and post-Promise initiation. Columns 1 and 2 in each panel show covariate means pre- and post-Promise, respectively. Columns 3 and 4 in each panel show the difference in the pre-and post-Promise means and p-value from two-sided t-tests of mean equivalence, respectively. Differences shown as percentage points, dollars, or ACT points, depending on the unit for the covariate. * p<0.05 **p<0.01 ***p<0.001.

Table 3- 6 Descriptive Statistics of Outcomes, Pre- and Post-Promise, by First-Generation Status

	Panel A: First-Generation				Panel B: Non-First-Generation			
	Pre-Promise	Post-Promise	Difference	P-Value	Pre-Promise	Post-Promise	Difference	P-Value
First-Term Outcomes								
Credits Attempted	13.39	14.08	0.69	0	13.89	14.39	0.5	0
Credits Earned	11.13	11.66	0.53	0	12.06	12.52	0.45	0
Percent Credits Earned	82.80%	82.69%	0.00	0.461	86.50%	86.85%	0.00	0.059
GPA	2.54	2.50	-0.04	0	2.72	2.75	0.02	0.002
N Observations	70,835	50,501			42,685	23,096		

Note: Table shows first-term difference in means for first-generation (Panel A) and non-first-generation students (Panel B), pre- and post-Promise initiation. Columns 1 and 2 in each panel show covariate means pre- and post-Promise, respectively. Columns 3 and 4 in each panel show the difference in the pre-and post-Promise means and p-value from two-sided t-tests of mean equivalence, respectively. Differences shown as number of credits, percentage points, or GPA points, depending on the unit for the covariate. * p<0.05 **p<0.01 ***p<0.001.

Figure 3- 2 First-Term Outcomes by First-Generation Status, Pre- and Post-Promise



Note: Figures show changes in outcomes in the sample over time by students' first-generation status. Outcomes in the sample aggregated within a given school year. Linear fit lines displayed.

Table 3- 7 Descriptive Statistics of Predictors, Post-Promise, by First-Generation and Tennessee Promise Student Status

	Panel A: First-Generation, Post-Promise				Panel B: Non-First-Generation, Post-Promise			
	Non-TN Promise Student	TN Promise Student	Difference	P-Value	Non-TN Promise Student	TN Promise Student	Difference	P-Value
Demographic Characteristics								
Male	42.07%	40.76%	-0.01	0.005	49.16%	49.76%	0.01	0.433
Female	57.93%	59.24%	0.01	0.005	50.84%	50.24%	-0.01	0.433
White	61.20%	74.51%	0.13	0	74.10%	79.61%	0.06	0
Black	24.89%	13.88%	-0.11	0	15.07%	11.18%	-0.04	0
Latinx	5.47%	4.73%	-0.01	0	2.57%	2.79%	0	0.363
Asian	1.85%	0.86%	-0.01	0	2.22%	1.05%	-0.01	0
Other	6.58%	6.03%	-0.01	0.017	6.05%	5.37%	-0.01	0.059
Academic Preparedness								
ACT Composite	20.33	19.03	-1.3	0	22.48	19.94	-2.54	0
ACT Composite (Bottom 25%)	34.26%	46.01%	0.12	0	17.12%	34.78%	0.18	0
ACT Composite (25-50%]	28.99%	31.39%	0.02	0	25.05%	34.01%	0.09	0
ACT Composite (50-75%]	21.89%	16.35%	-0.06	0	27.27%	21.68%	-0.06	0
ACT Composite (Top 25%)	14.87%	6.25%	-0.09	0	30.56%	9.54%	-0.21	0
Never Dual Enrolled	93.62%	96.88%	0.03	0	87.59%	94.18%	0.07	0
Dual Enrolled	6.38%	3.12%	-0.03	0	12.41%	5.82%	-0.07	0
Financial Resources								
Student AGI	$1,968	$1,805	- $162	0.122	$2,707	$1,624	- $1,082	0.249
Parent AGI	$55,668	$58,067	$2,399	0.003	$121,918	$93,976	- $27,941	0
Parent EFC	$11,058	$9,998	- $1,059	0.006	$39,547	$23,827	- $15,720	0
Parental EFC < $6,000	65.61%	55.46%	-0.1	0	29.95%	28.06%	-0.02	0.007
Parental EFC $6,000-21,000	20.27%	31.04%	0.11	0	23.73%	35.12%	0.11	0
Parental EFC $21,000-75,000	11.90%	12.44%	0.01	0.082	33.12%	31.27%	-0.02	0.009
Parental EFC $75,000 +	2.23%	1.06%	-0.01	0	13.20%	5.55%	-0.08	0
Pell Eligible	65.54%	55.54%	-0.1	0	30.79%	29.37%	-0.01	0.043

TSAA Grant Eligible	48.61%	42.05%	-0.07	0	19.52%	18.84%	-0.01	0.255
HOPE Access Eligible	1.34%	1.11%	0	0.035	0.47%	0.49%	0	0.835
HOPE Aspire Eligible	27.32%	19.00%	-0.08	0	11.40%	8.21%	-0.03	0
HOPE GAM Eligible	1.84%	0.13%	-0.02	0	6.34%	0.24%	-0.06	0
HOPE Eligible	37.61%	38.75%	0.01	0.015	62.24%	55.55%	-0.07	0
Institutional								
Community College	41.93%	96.58%	0.55	0	26.30%	96.58%	0.7	0
Four-Year College	58.07%	3.42%	-0.55	0	73.70%	3.42%	-0.7	0
Unknown/General Major	45.08%	68.25%	0.23	0	40.67%	73.77%	0.33	0
Arts/Humanities Major	7.36%	4.21%	-0.03	0	6.93%	4.10%	-0.03	0
Business Major	7.68%	4.47%	-0.03	0	10.52%	3.85%	-0.07	0
Health/Medicine Major	16.18%	14.25%	-0.02	0	13.04%	9.87%	-0.03	0
STEM Major	12.76%	2.23%	-0.11	0	17.38%	2.20%	-0.15	0
Social Sciences Major	7.99%	3.06%	-0.05	0	9.01%	2.96%	-0.06	0
Trade Major	2.94%	3.54%	0.01	0	2.44%	3.24%	0.01	0.001
N Observations	34,569	15,932			17,362	5,734		

Note: Table shows first-term difference in means for first-generation (Panel A) and non-first-generation students (Panel B), following Promise initiation, by take-up of Tennessee Promise. Columns 1 and 2 in each panel show covariate means for non-Tennessee Promise and Tennessee Promise scholars, post-Promise, respectively. Columns 3 and 4 in each panel shows the difference in means between TPS and non-TPS students and p-value from two-sided t-tests of mean equivalence, respectively. Differences shown as percentage points, dollars, or ACT points, depending on the unit for the covariate. * p<0.05 **p<0.01 ***p<0.001.

Table 3- 8 Descriptive Statistics of Outcomes, Post-Promise, by First-Generation and Tennessee Promise Student Status

	Panel A: First-Generation, Post-Promise				Panel B: Non-First-Generation, Post-Promise			
	Non-TPS	TPS	Difference	P-Value	Non-TPS	TPS	Difference	P-Value
First-Term Outcomes								
Credits Attempted	14.16	13.90	-0.27	0	14.48	14.14	-0.34	0
Credits Earned	11.78	11.41	-0.37	0	12.70	11.96	-0.75	0
Percent Credits Earned	82.94%	82.15%	-0.01	0.001	87.59%	84.61%	-0.03	0
GPA	2.52	2.46	-0.07	0	2.79	2.60	-0.19	0
N Observations	34,569	15,932			17,362	5,734		

Note: Table shows first-term difference in means for first-generation (Panel A) and non-first-generation students (Panel B), following Promise initiation, by take-up of Tennessee Promise. Columns 1 and 2 in each panel show covariate means for non-Tennessee Promise and Tennessee Promise scholars, post-Promise, respectively. Columns 3 and 4 in each panel shows the difference in means between TPS and non-TPS students and p-value from two-sided t-tests of mean equivalence, respectively. Differences shown as number of credits, percentage points, or GPA points, depending on the unit for the covariate.
* p<0.05 **p<0.01 ***p<0.001.

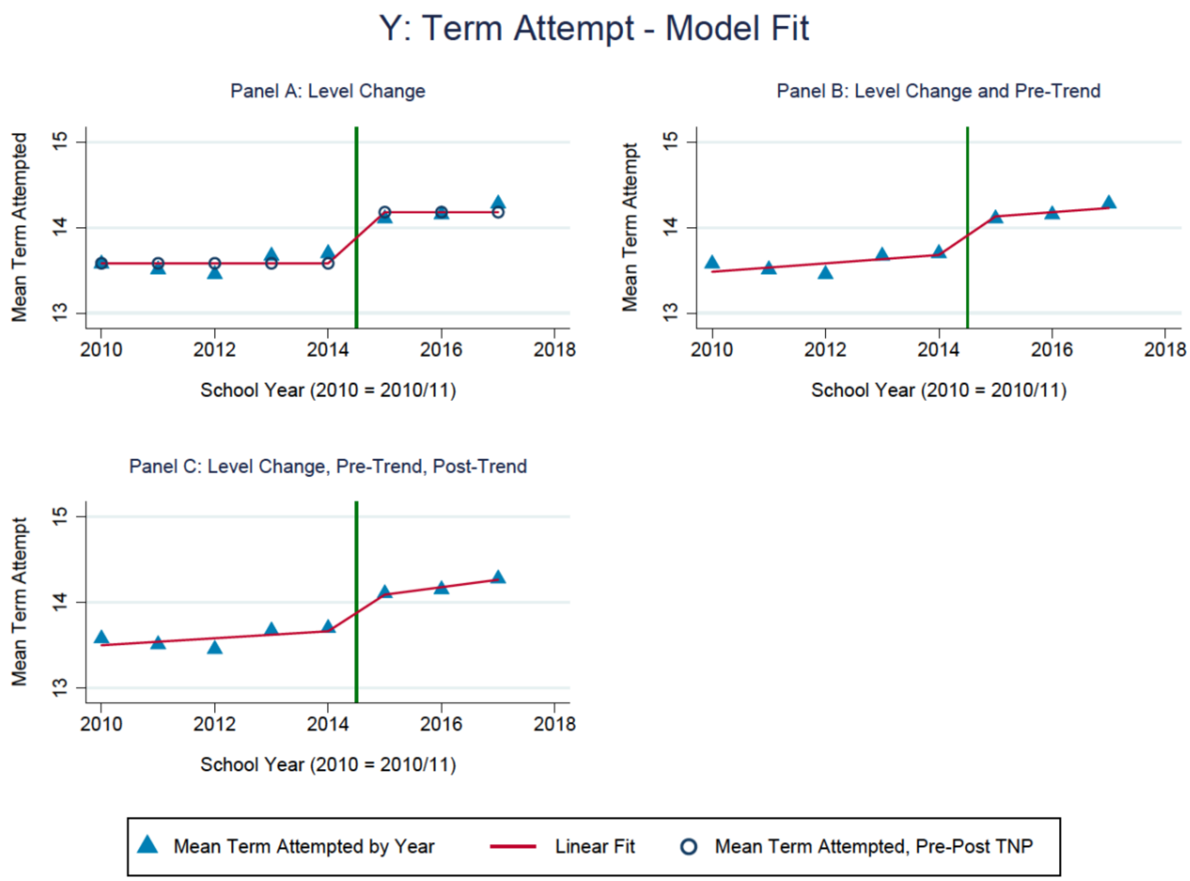
Table 3- 9 Naïve Model Building

	Panel A: FG			Panel B: Non-FG			Panel C: Full Sample		
		Term Attempted			Term Attempted			Term Attempted	
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Level Change	0.687***	0.505**	0.409*	0.501***	0.309	0.281*	0.598***	0.401*	0.341*
	(0.136)	(0.169)	(0.170)	(0.130)	(0.159)	(0.126)	(0.135)	(0.167)	(0.154)
Pre-Trend		0.045*	0.030		0.049**	0.046		0.049**	0.041
		(0.018)	(0.021)		(0.017)	(0.023)		(0.017)	(0.022)
Slope Change			0.076			0.021			0.046
			(0.051)			(0.053)			(0.051)
Constant	13.393***	13.484***	13.455***	13.893***	13.989***	13.982***	13.581***	13.679***	13.662***
	(0.274)	(0.291)	(0.297)	(0.259)	(0.270)	(0.278)	(0.276)	(0.290)	(0.297)
Adj. R2	0.025	0.025	0.026	0.014	0.014	0.014	0.019	0.020	0.020
		Term Earned			Term Earned			Term Earned	
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Level Change	0.529***	0.053	0.187	0.452*	-0.073	0.078	0.447*	-0.062	0.114
	(0.137)	(0.180)	(0.208)	(0.216)	(0.154)	(0.198)	(0.166)	(0.173)	(0.203)
Pre-Trend		0.118***	0.138***		0.134**	0.152**		0.127***	0.152***
		(0.031)	(0.032)		(0.036)	(0.045)		(0.030)	(0.033)
Slope Change			-0.106			-0.113			-0.137*
			(0.061)			(0.072)			(0.060)
Constant	11.133***	11.371***	11.412***	12.065***	12.325***	12.360***	11.483***	11.737***	11.786***
	(0.335)	(0.356)	(0.352)	(0.427)	(0.398)	(0.390)	(0.383)	(0.388)	(0.381)
Adj. R2	0.004	0.006	0.006	0.003	0.005	0.005	0.003	0.005	0.005

	Term GPA			Term GPA			Term GPA		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Level Change	-0.040	-0.124***	-0.103***	0.024	-0.077*	-0.069	-0.031	-0.123***	-0.096**
	(0.027)	(0.025)	(0.026)	(0.027)	(0.034)	(0.038)	(0.026)	(0.027)	(0.028)
Pre-Trend		0.021***	0.024***		0.026***	0.027**		0.023***	0.027***
		(0.004)	(0.005)		(0.006)	(0.008)		(0.004)	(0.005)
Slope Change			-0.017			-0.006			-0.021
			(0.017)			(0.018)			(0.015)
Constant	2.543***	2.585***	2.591***	2.721***	2.771***	2.773***	2.610***	2.655***	2.663***
	(0.037)	(0.038)	(0.037)	(0.081)	(0.076)	(0.072)	(0.058)	(0.057)	(0.055)
Adj. R2	0.000	0.001	0.001	0.000	0.001	0.001	0.000	0.001	0.001
	Percent Credits Earned			Percent Credits Earned			Percent Credits Earned		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Level Change	-0.109	-2.432**	-0.923	0.349	-2.258***	-0.932	-0.196	-2.671***	-1.043
	(0.557)	(0.641)	(0.945)	(0.980)	(0.497)	(0.886)	(0.701)	(0.560)	(0.888)
Pre-Trend		0.573**	0.803***		0.668*	0.826*		0.619**	0.847**
		(0.179)	(0.210)		(0.272)	(0.359)		(0.195)	(0.249)
Slope Change			-1.201*			-0.988			-1.262*
			(0.466)			(0.611)			(0.482)
Constant	82.798***	83.956***	84.420***	86.500***	87.795***	88.100***	84.190***	85.421***	85.873***
	(0.965)	(0.968)	(0.920)	(1.660)	(1.286)	(1.165)	(1.286)	(1.154)	(1.069)
Adj. R2	-0.000	0.001	0.001	0.000	0.001	0.002	0.000	0.001	0.002
N	121,336	121,336	121,336	65,781	65,781	65,781	187,117	187,117	187,117

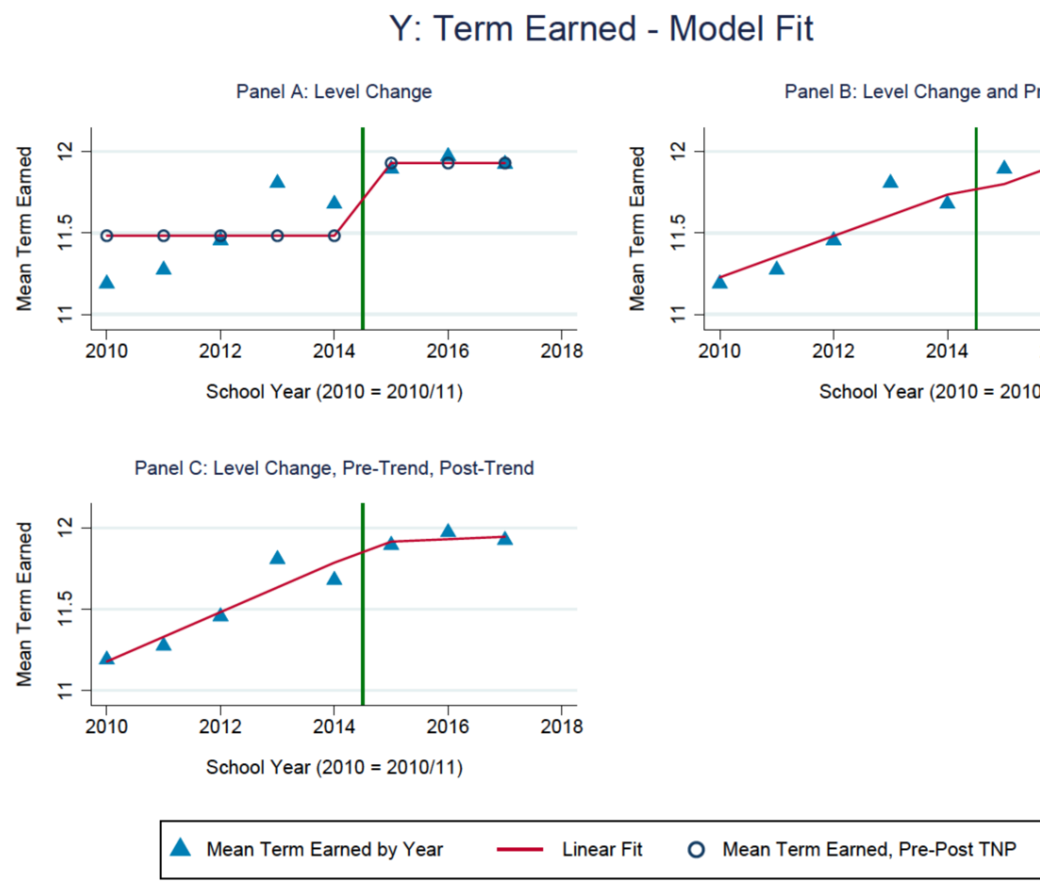
Note: Table displays naïve pre- and post-Promise estimates of outcome (column 1 in each panel), adding controls for the pre-Promise trends (column 2 in each panel), and the post-Promise slope change (column 3 in each column). Standard errors in parentheses. * p<0.05 **p<0.01 ***p<0.001

Figure 3- 3 Naïve Model Building, Y: Term Credits Attempted



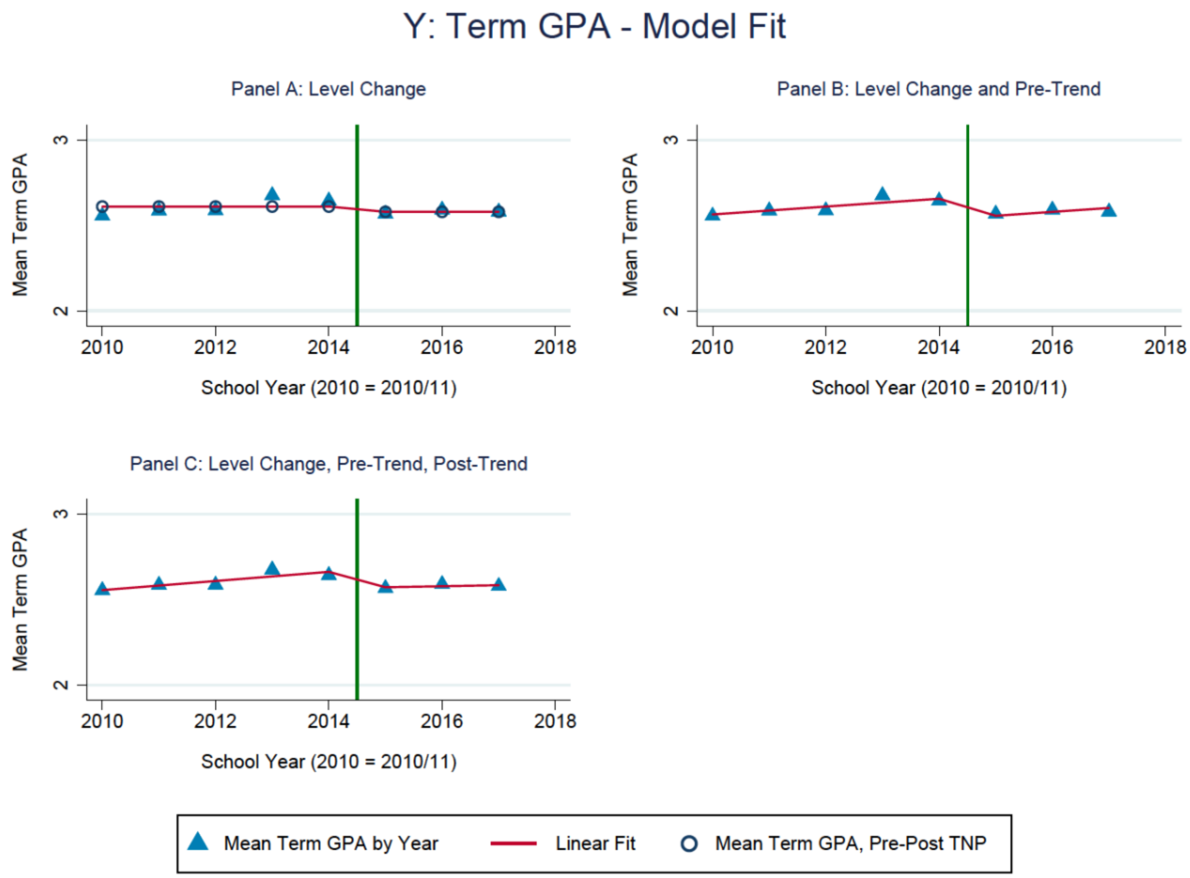
Note: Panel A shows a naïve ITS model with a binary indicator for the pre-post intervention. Panel B includes a time trend, and Panel C adds in a post-intervention trend. Blue triangles represent the mean term credits attempted within a given school year. Open circles in Panel A illustrate how, without a control for the pre- and post-intervention trend, the model assumes a constant pre- and post-intervention slope. Fitted lines corresponding with the regressions in Table 3-9, Panel C (Full Sample) shown in red.

Figure 3- 4 Naïve Model Building, Y: Term Credits Earned



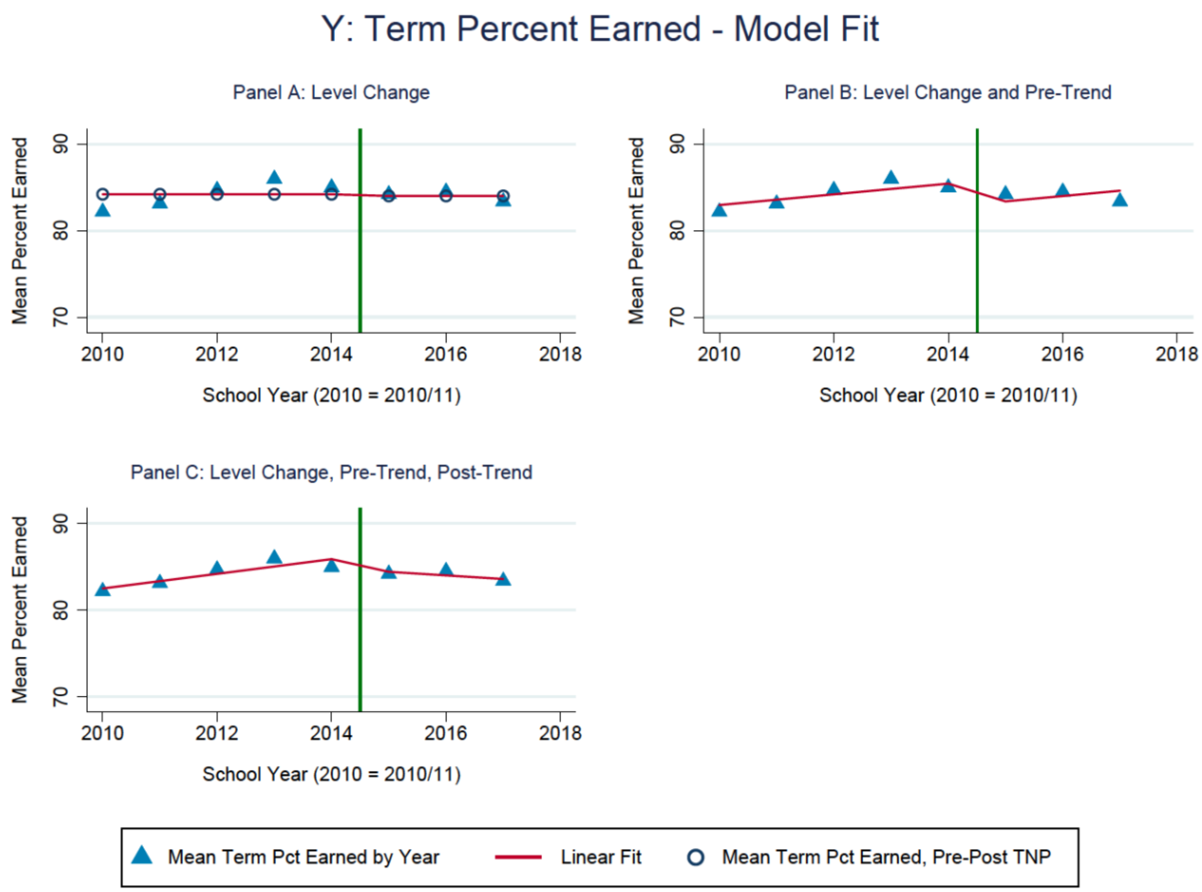
Note: Panel A shows a naïve ITS model with a binary indicator for the pre-post intervention. Panel B includes a time trend, and Panel C adds in a post-intervention trend. Blue triangles represent the mean term credits earned within a given school year. Open circles in Panel A illustrate how, without a control for the pre- and post-intervention trend, the model assumes a constant pre- and post-intervention slope. Fitted lines corresponding with the regressions in Table 3-9, Panel C (Full Sample) shown in red.

Figure 3- 5 Naïve Model Building, Y: Term GPA



Note: Panel A shows a naïve ITS model with a binary indicator for the pre-post intervention. Panel B includes a time trend, and Panel C adds in a post-intervention trend. Blue triangles represent the mean term GPA within a given school year. Open circles in Panel A illustrate how, without a control for the pre- and post-intervention trend, the model assumes a constant pre- and post-intervention slope. Fitted lines corresponding with the regressions in Table 3-9, Panel C (Full Sample) shown in red.

Figure 3- 6 Naïve Model Building, Y: Percent Credits Earned



Note: Panel A shows a naïve ITS model with a binary indicator for the pre-post intervention. Panel B includes a time trend, and Panel C adds in a post-intervention trend. Blue triangles represent the mean percent of credits earned within a given school year. Open circles in Panel A illustrate how, without a control for the pre- and post-intervention trend, the model assumes a constant pre- and post-intervention slope. Fitted lines corresponding with the regressions in Table 3-9, Panel C (Full Sample) shown in red.

Table 3- 10 Estimates of First-Term Outcomes by First-Generation Status

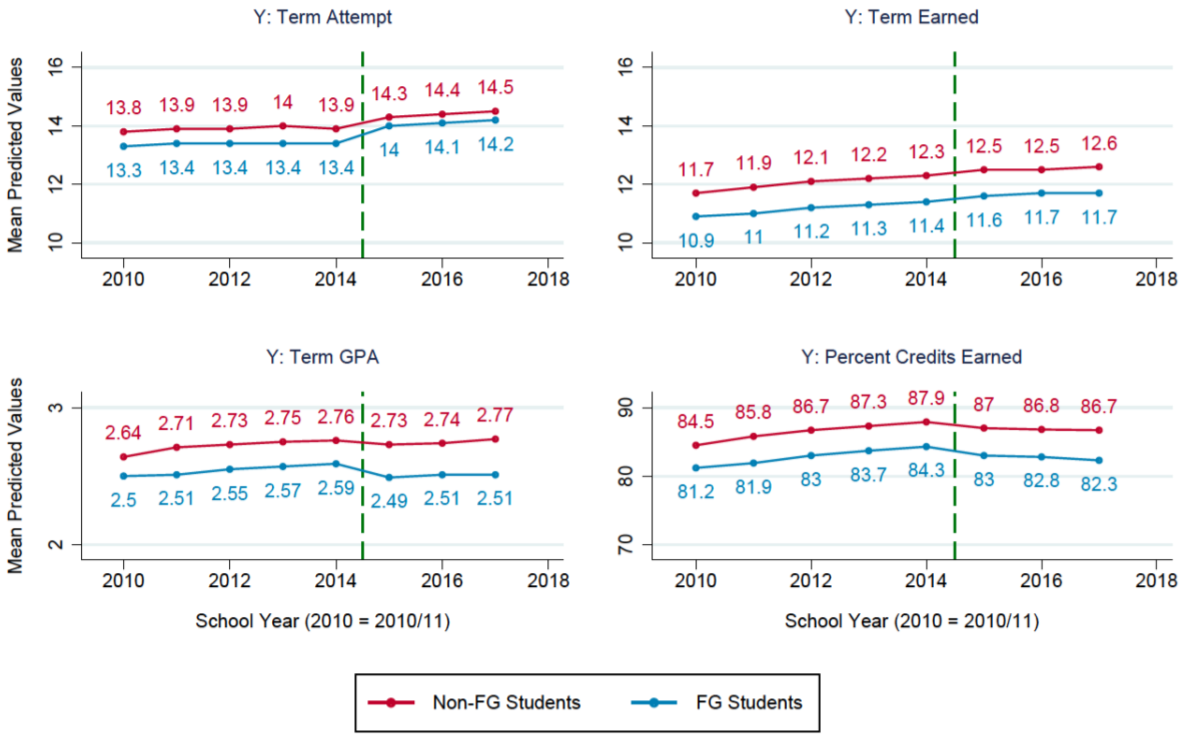
	Panel A: Full Sample											
	Term Attempt			Term Earned			Term GPA			Percent Credits Earned		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	0.654***	0.512**	0.597**	0.481*	0.355	0.433*	-0.072*	-0.037	-0.058*	-0.273	-0.375	-0.292
	(0.166)	(0.147)	(0.160)	(0.197)	(0.201)	(0.195)	(0.027)	(0.029)	(0.025)	(0.864)	(0.803)	(0.800)
Pre-Trend	0.017	0.040*	0.025	0.097**	0.126*	0.108**	0.014*	0.017	0.015*	0.579*	0.668	0.614*
	(0.022)	(0.018)	(0.020)	(0.034)	(0.046)	(0.037)	(0.005)	(0.009)	(0.007)	(0.213)	(0.368)	(0.263)
Slope Change	0.051	-0.014	0.031	-0.097	-0.124	-0.106	-0.006	-0.001	-0.006	-0.967	-0.842	-0.938
	(0.041)	(0.041)	(0.040)	(0.065)	(0.070)	(0.065)	(0.017)	(0.017)	(0.017)	(0.479)	(0.617)	(0.519)
Constant	11.986***	12.097***	12.060***	9.097***	9.611***	9.407***	1.829***	1.889***	1.892***	76.144***	79.906***	78.135***
	(0.199)	(0.174)	(0.184)	(0.265)	(0.319)	(0.266)	(0.092)	(0.095)	(0.090)	(1.810)	(1.957)	(1.736)
Adj. R2	0.273	0.251	0.271	0.185	0.190	0.195	0.126	0.144	0.139	0.089	0.087	0.093
N	121,336	65,781	187,117	121,336	65,781	187,117	121,336	65,781	187,117	121,336	65,781	187,117

Panel B: Sample Excluding Tennessee Promise Students

	Term Attempt			Term Earned			Term GPA			Percent Credits Earned		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	0.443**	0.303**	0.387**	0.223	0.120	0.182	-0.078*	-0.030	-0.059	-0.901	-0.815	-0.872
	(0.141)	(0.089)	(0.122)	(0.182)	(0.168)	(0.171)	(0.034)	(0.032)	(0.029)	(0.893)	(0.936)	(0.866)
Pre-Trend	0.017	0.041*	0.026	0.098**	0.127*	0.109**	0.014*	0.016	0.015*	0.578*	0.666	0.612*
	(0.022)	(0.018)	(0.020)	(0.034)	(0.047)	(0.037)	(0.005)	(0.009)	(0.006)	(0.212)	(0.367)	(0.262)
Slope Change	0.068	-0.006	0.044	-0.044	-0.080	-0.055	0.003	0.003	0.003	-0.695	-0.590	-0.659
	(0.046)	(0.052)	(0.047)	(0.077)	(0.067)	(0.071)	(0.019)	(0.017)	(0.018)	(0.532)	(0.642)	(0.568)
Constant	11.967***	12.118***	12.053***	9.048***	9.628***	9.379***	1.836***	1.904***	1.901***	75.791***	79.850***	77.895***
	(0.207)	(0.179)	(0.192)	(0.282)	(0.334)	(0.282)	(0.095)	(0.099)	(0.093)	(1.867)	(2.048)	(1.799)
Adj. R2	0.298	0.276	0.296	0.197	0.200	0.208	0.123	0.145	0.138	0.088	0.087	0.093
N	105,404	60,047	165,451	105,404	60,047	165,451	105,404	60,047	165,451	105,404	60,047	165,451

Note: Models in Panel A present estimates using the full sample of students and models in Panel B present estimates using the sample excluding Tennessee Promise Students (TPS). Models include controls for demographic characteristics, academic preparedness, financial resources, and institution and major fixed effects. The first two columns within each outcome present estimates from subgroup models by first-generation status. The last column within each outcome present estimates using the pooled sample. Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Figure 3- 7 Linear Predictions of First-Term Outcomes, by First-Generation Status



Note: Models display predicted values from subgroup models shown in Table 3-10, Panel A, for each outcome. Model predictions aggregated by school-year and by first-generation status. Models include controls for student demographic characteristics, academic preparedness, and access to financial resources, as well as institution and major fixed effects.

Table 3- 11 Estimates of First-Term Outcomes by First-Generation Status; Level Change as Categorical Variable

	Term Attempt			Term Earned			Term GPA			Percent Credits Earned		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Post Yr 1 (2015)	0.719***	0.499**	0.638***	0.370*	0.198	0.307	-0.085**	-0.041	-0.069*	-1.421*	-1.472**	-1.440*
	(0.165)	(0.164)	(0.165)	(0.167)	(0.155)	(0.158)	(0.027)	(0.034)	(0.028)	(0.643)	(0.501)	(0.565)
Post Yr 2 (2016)	0.728**	0.482*	0.638**	0.310	0.179	0.260	-0.071	-0.034	-0.057	-1.855*	-1.507*	-1.744*
	(0.192)	(0.194)	(0.193)	(0.189)	(0.171)	(0.178)	(0.036)	(0.036)	(0.035)	(0.706)	(0.718)	(0.701)
Post Yr 3 (2017)	0.819***	0.472*	0.700**	0.177	-0.054	0.094	-0.098	-0.043	-0.080	-3.343**	-3.188*	-3.313**
	(0.198)	(0.220)	(0.205)	(0.182)	(0.158)	(0.167)	(0.048)	(0.058)	(0.051)	(0.981)	(1.350)	(1.108)
Pre-Trend	0.017	0.040*	0.025	0.097**	0.126*	0.108**	0.014*	0.017	0.015*	0.579*	0.668	0.614*
	(0.022)	(0.018)	(0.020)	(0.034)	(0.046)	(0.037)	(0.005)	(0.009)	(0.007)	(0.213)	(0.368)	(0.263)
Constant	11.989***	12.098***	12.062***	9.094***	9.606***	9.403***	1.828***	1.888***	1.891***	76.107***	79.871***	78.098***
	(0.199)	(0.174)	(0.184)	(0.264)	(0.319)	(0.265)	(0.091)	(0.095)	(0.089)	(1.798)	(1.956)	(1.727)
Wald Tests												
2015 v. 2016	0.874	0.722	0.998	0.578	0.831	0.617	0.582	0.699	0.595	0.536	0.953	0.625
2015 v. 2017	0.242	0.736	0.442	0.154	0.087	0.118	0.721	0.944	0.744	0.059	0.181	0.085
2016 v. 2017	0.072	0.857	0.188	0.126	**0.017**	0.051	0.275	0.764	0.383	**0.014**	0.052	**0.017**
Adj. R2	0.273	0.251	0.271	0.185	0.190	0.195	0.126	0.144	0.139	0.089	0.087	0.093
N	121,336	65,781	187,117	121,336	65,781	187,117	121,336	65,781	187,117	121,336	65,781	187,117

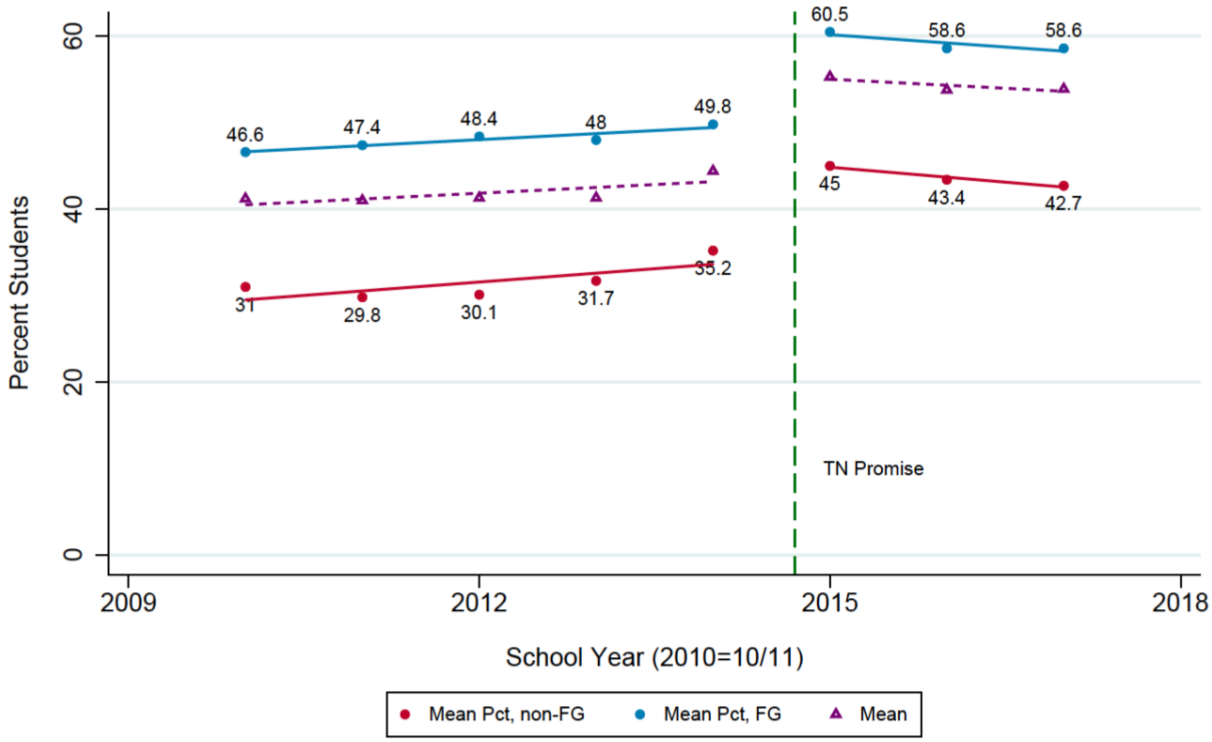
Note: Models present estimates using the full sample of students. The level-change and slope-change variables are replaced by a categorical variable equal to 0 in the pre-Promise period and 1, 2, and 3, in each post-Promise year, respectively. Models include controls for demographic characteristics, academic preparedness, financial resources, and institution and major fixed effects. The first two columns within each outcome present estimates from subgroup models by first-generation status. The last column within each outcome present estimates using the pooled sample. Standard errors clustered by institution and are in parentheses.
* p<0.05 **p<0.01 ***p<0.001.

Table 3- 12 Estimates of First-Term Outcomes Excluding Tennessee Promise Students by First-Generation Status; Level Change as Categorical Variable

	Term Attempt			Term Earned			Term GPA			Percent Credits Earned		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Post Yr 1 (2015)	0.390**	0.168*	0.307**	0.048	-0.104	-0.009	-0.073*	-0.018	-0.052	-1.882**	-1.694**	-1.816**
	(0.123)	(0.081)	(0.108)	(0.136)	(0.113)	(0.119)	(0.033)	(0.030)	(0.029)	(0.596)	(0.479)	(0.509)
Post Yr 2 (2016)	0.718**	0.480*	0.632**	0.289	0.171	0.244	-0.073	-0.038	-0.061	-1.957*	-1.569*	-1.831*
	(0.191)	(0.193)	(0.191)	(0.187)	(0.170)	(0.176)	(0.035)	(0.035)	(0.034)	(0.696)	(0.702)	(0.688)
Post Yr 3 (2017)	0.525**	0.134	0.387*	-0.041	-0.291*	-0.129	-0.067	-0.010	-0.046	-3.275**	-2.926*	-3.154**
	(0.163)	(0.159)	(0.163)	(0.159)	(0.116)	(0.134)	(0.050)	(0.050)	(0.050)	(0.988)	(1.142)	(1.045)
Pre-Trend	0.018	0.042*	0.027	0.098**	0.128*	0.109**	0.013*	0.016	0.015*	0.579*	0.666	0.613*
	(0.021)	(0.017)	(0.020)	(0.034)	(0.047)	(0.037)	(0.005)	(0.009)	(0.006)	(0.212)	(0.367)	(0.262)
Constant	11.962***	12.114***	12.048***	9.042***	9.623***	9.375***	1.836***	1.904***	1.901***	75.778***	79.841***	77.885***
	(0.207)	(0.179)	(0.192)	(0.282)	(0.336)	(0.282)	(0.095)	(0.098)	(0.092)	(1.865)	(2.052)	(1.799)
Wald Tests												
2015 v. 2016	**0.006**	**0.036**	**0.010**	0.136	0.083	0.096	0.988	0.311	0.700	0.922	0.878	0.985
2015 v. 2017	0.158	0.729	0.398	0.566	0.179	0.404	0.871	0.830	0.880	0.204	0.349	0.251
2016 v. 2017	**0.022**	**0.007**	**0.011**	**0.014**	**0.003**	**0.004**	0.821	0.282	0.598	0.051	0.052	**0.042**
Adj. R2	0.299	0.278	0.297	0.198	0.201	0.209	0.123	0.145	0.138	0.088	0.087	0.093
N	105,404	60,047	165,451	105,404	60,047	165,451	105,404	60,047	165,451	105,404	60,047	165,451

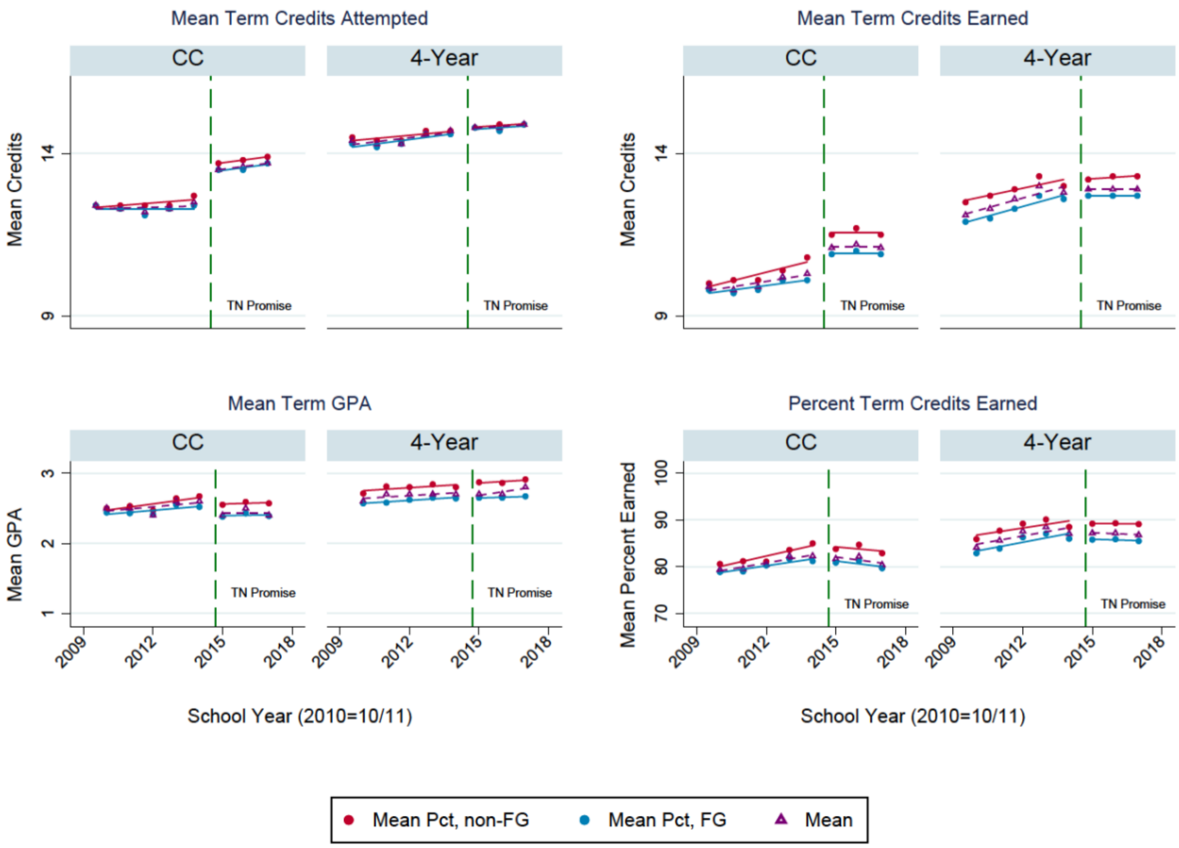
Note: Models present estimates using the sample excluding Tennessee Promise Students (TPS). The level-change and slope-change variables are replaced by a categorical variable equal to 0 in the pre-Promise period and 1, 2, and 3, in each post-Promise year, respectively. Models include controls for demographic characteristics, academic preparedness, financial resources, and institution and major fixed effects. The first two columns within each outcome present estimates from subgroup models by first-generation status. The last column within each outcome present estimates using the pooled sample. Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Figure 3- 8 Community College Enrollment, Pre- and Post-Promise, by First-Generation Status



Note: Figure shows percent of students in the sample within a given school year who enroll in a community college in their first term out of all students enrolling in community colleges or four-year public universities in Tennessee. Percentages shown by students' first-generation status, as well as the mean percent in each school year. Linear fit lines displayed.

Figure 3- 9 Mean First-Term Outcomes by First-Generation Status and Institution Type, Pre- and Post-Promise



Note: Figures show means of each outcome over time aggregated by school year. Means displayed by students' first-generation status and enrollment in a community or four-year college in their first-term. The mean for each outcome within a school also displayed in purple. Linear fit lines displayed.

Table 3- 13 Estimates of First-Term Outcomes by First-Generation Status and Institution Type

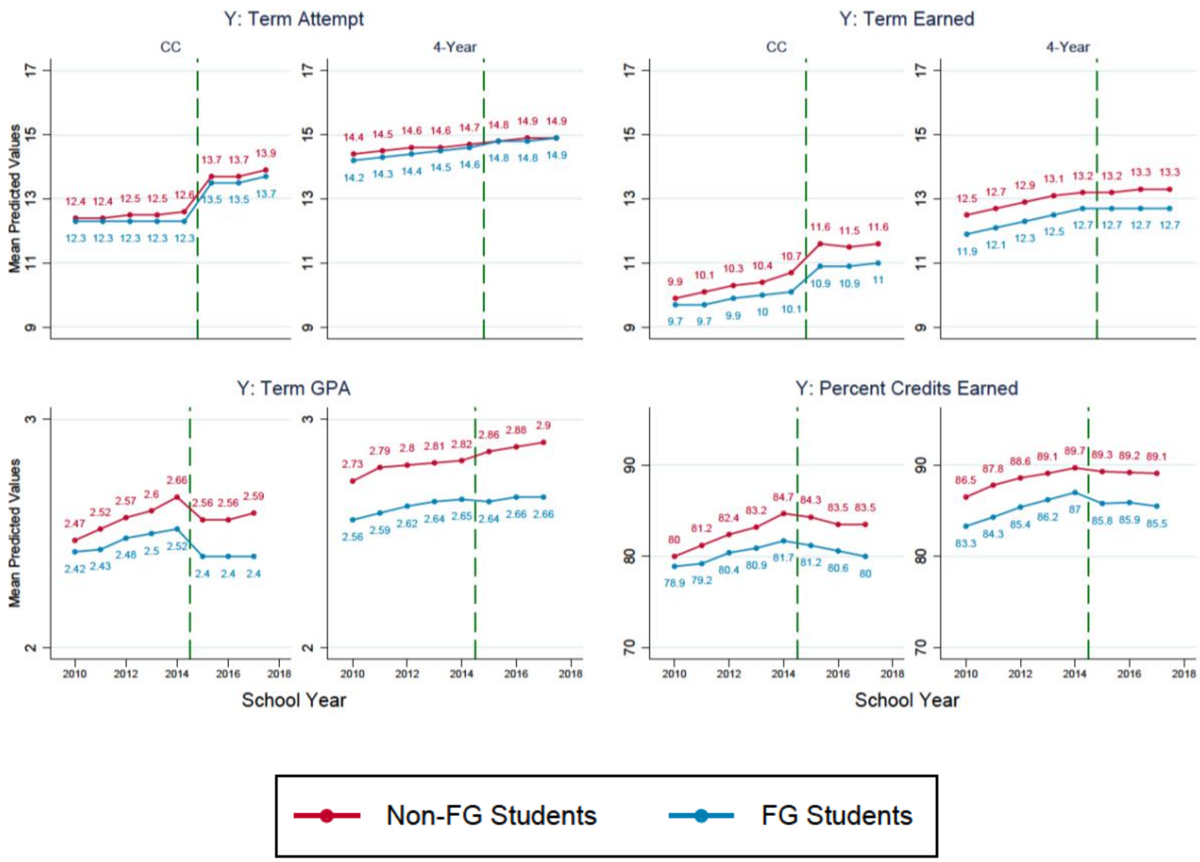
	Panel A											
	Term Attempted						Term Earned					
	Community College			4-Year			Community College			4-Year		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	1.077***	1.093***	1.080***	0.164	0.127*	0.144	0.880**	0.906**	0.891**	0.032	-0.015	0.009
	(0.211)	(0.178)	(0.200)	(0.101)	(0.052)	(0.078)	(0.265)	(0.252)	(0.258)	(0.163)	(0.165)	(0.157)
Pre-Trend	-0.041	-0.001	-0.030	0.072**	0.060*	0.067**	0.021	0.099*	0.043	0.164*	0.136	0.153*
	(0.028)	(0.029)	(0.027)	(0.020)	(0.018)	(0.019)	(0.031)	(0.040)	(0.033)	(0.054)	(0.073)	(0.062)
Slope Change	0.109	0.026	0.086	-0.011	-0.035	-0.019	-0.050	-0.144	-0.078	-0.133	-0.104	-0.119
	(0.059)	(0.060)	(0.057)	(0.046)	(0.054)	(0.047)	(0.084)	(0.101)	(0.086)	(0.097)	(0.093)	(0.095)
Constant	9.857***	10.255***	10.763***	12.262***	12.213***	12.528***	7.633***	8.316***	8.074***	9.096***	9.817***	9.682***
	(0.174)	(0.212)	(0.232)	(0.290)	(0.261)	(0.220)	(0.273)	(0.336)	(0.327)	(0.489)	(0.561)	(0.438)
Adj. R2	0.184	0.183	0.184	0.104	0.083	0.096	0.153	0.164	0.158	0.098	0.094	0.102

Panel B

	Term GPA						Percent Credits Earned					
	Community College			4-Year			Community College			4-Year		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	-0.125**	-0.109*	-0.119**	0.004	0.010	0.007	0.177	0.165	0.197	-0.738	-0.803	-0.764
	(0.033)	(0.043)	(0.034)	(0.035)	(0.038)	(0.029)	(1.304)	(1.301)	(1.259)	(0.960)	(1.015)	(0.936)
Pre-Trend	0.013	0.030*	0.018*	0.012	0.008	0.011	0.366*	0.772**	0.481**	0.744	0.589	0.681
	(0.007)	(0.010)	(0.008)	(0.008)	(0.012)	(0.010)	(0.138)	(0.202)	(0.151)	(0.395)	(0.547)	(0.461)
Slope Change	-0.010	-0.022	-0.014	-0.004	0.009	0.001	-0.945	-1.309*	-1.059	-0.875	-0.517	-0.728
	(0.024)	(0.024)	(0.023)	(0.023)	(0.021)	(0.022)	(0.579)	(0.586)	(0.564)	(0.763)	(0.870)	(0.823)
Constant	1.969***	2.033***	1.910***	1.493***	1.698***	1.701***	77.853***	81.246***	76.016***	75.685***	81.315***	78.347***
	(0.093)	(0.077)	(0.094)	(0.153)	(0.144)	(0.124)	(2.086)	(1.848)	(2.088)	(3.691)	(3.729)	(2.999)
Adj. R2	0.115	0.111	0.117	0.130	0.150	0.145	0.086	0.079	0.086	0.074	0.073	0.078
N	63,900	23,569	87,469	57,436	42,212	99,648	63,900	23,569	87,469	57,436	42,212	99,648

Note: Models present estimates using the full sample of students. Columns show results from subgroup models by institution type and students' first-generation status. Within a given outcome, the following models: (1) FG in CC, (2) Non-FG in a CC, (3) All students in a CC, (4) FG in a 4-year, (5) Non-FG in a 4-year, and (6) All students in a 4-year. Models include controls for demographic characteristics, academic preparedness, financial resources, and institution and major fixed effects within institution type. Since subgroup models are estimated, institution fixed effects include dummy variables for individual institutions attended within each institution type. Standard errors clustered by institution and are in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Figure 3- 10 Linear Predictions of First-Term Outcomes by First-Generation Status and Institution Type



Note: Models display predicted values from subgroup models shown in Table 3-13, Panel A, for each outcome. Model predictions aggregated by school-year, first-generation status, and institution of enrollment. Models include controls for student demographic characteristics, academic preparedness, and access to financial resources, as well as institution and major fixed effects. Since subgroup models are estimated, institution fixed effects include dummy variables for individual institutions attended within each institution type.

Table 3- 14 Estimates of First-Term Outcomes Excluding Tennessee Promise Students, by First-Generation Status and Institution Type

	Panel A											
	Term Attempted						Term Earned					
	Community College			4-Year			Community College			4-Year		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	0.728*	0.675**	0.708*	0.156	0.129*	0.140	0.428	0.469	0.438	0.020	-0.024	-0.002
	(0.288)	(0.211)	(0.265)	(0.099)	(0.051)	(0.077)	(0.406)	(0.431)	(0.401)	(0.164)	(0.159)	(0.154)
Pre-Trend	-0.043	-0.002	-0.032	0.071**	0.060*	0.067**	0.021	0.098*	0.042	0.164*	0.137	0.153*
	(0.028)	(0.029)	(0.027)	(0.020)	(0.018)	(0.019)	(0.030)	(0.039)	(0.032)	(0.054)	(0.073)	(0.062)
Slope Change	0.176	0.093	0.155	-0.005	-0.037	-0.015	0.058	-0.035	0.031	-0.124	-0.098	-0.111
	(0.095)	(0.098)	(0.093)	(0.047)	(0.055)	(0.049)	(0.152)	(0.180)	(0.156)	(0.097)	(0.090)	(0.093)
Constant	9.636***	10.076***	10.556***	12.276***	12.224***	12.536***	7.285***	8.100***	7.860***	9.075***	9.793***	9.661***
	(0.163)	(0.207)	(0.216)	(0.281)	(0.257)	(0.215)	(0.283)	(0.364)	(0.342)	(0.486)	(0.559)	(0.434)
Adj. R2	0.151	0.150	0.151	0.103	0.083	0.095	0.145	0.156	0.150	0.098	0.094	0.102

Panel B

	Term GPA						Percent Credits Earned					
	Community College			4-Year			Community College			4-Year		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	-0.174**	-0.103	-0.155**	0.003	0.008	0.006	-1.048	-0.172	-0.809	-0.768	-0.864	-0.808
	(0.049)	(0.054)	(0.047)	(0.035)	(0.038)	(0.030)	(1.964)	(2.464)	(2.024)	(0.965)	(0.977)	(0.924)
Pre-Trend	0.013	0.030*	0.018*	0.012	0.008	0.011	0.371*	0.768**	0.484**	0.743	0.591	0.680
	(0.007)	(0.010)	(0.008)	(0.008)	(0.012)	(0.010)	(0.135)	(0.197)	(0.146)	(0.395)	(0.547)	(0.461)
Slope Change	0.007	-0.022	-0.001	-0.003	0.011	0.003	-0.547	-1.042	-0.689	-0.856	-0.478	-0.701
	(0.039)	(0.038)	(0.038)	(0.023)	(0.021)	(0.022)	(0.948)	(1.127)	(0.961)	(0.763)	(0.844)	(0.811)
Constant	1.992***	2.094***	1.973***	1.486***	1.692***	1.695***	76.428***	80.583***	75.520***	75.479***	81.105***	78.169***
	(0.095)	(0.075)	(0.094)	(0.152)	(0.143)	(0.122)	(2.095)	(2.229)	(2.188)	(3.598)	(3.659)	(2.914)
Adj. R2	0.107	0.104	0.108	0.130	0.150	0.146	0.084	0.076	0.084	0.074	0.073	0.078
N	48,513	18,031	66,544	56,891	42,016	98,907	48,513	18,031	66,544	56,891	42,016	98,907

Note: Models present estimates using the sample excluding Tennessee Promise Students (TPS). Columns show results from subgroup models by institution type and students' first-generation status. Within a given outcome, the following models: (1) FG in CC, (2) Non-FG in a CC, (3) All students in a CC, (4) FG in a 4-year, (5) Non-FG in a 4-year, and (6) All students in a 4-year. Models include controls for demographic characteristics, academic preparedness, financial resources, and institution and major fixed effects within institution type. Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Table 3- 15 Tests for Alternate Treatment in Years Before Promise (2012-2014)

	Term Attempted	Term Earned	Term GPA	Percent Credits Earned
	Panel A: Intervention Year - 2012			
Level Change	-0.318**	0.009	0.018	1.830**
	(0.094)	(0.091)	(0.018)	(0.609)
Slope Pre	-0.088	0.017	0.008	0.583
	(0.055)	(0.055)	(0.017)	(0.310)
Slope Change	0.302**	0.135	-0.009	-0.724
	(0.080)	(0.088)	(0.019)	(0.393)
Constant	11.975***	9.046***	1.848***	76.090***
	(0.164)	(0.257)	(0.080)	(1.787)
Adj. R2	0.269	0.195	0.139	0.093
	Panel B: Intervention Year - 2013			
Level Change	-0.014	0.170	0.073	1.331
	(0.076)	(0.098)	(0.040)	(0.797)
Pre-Trend	-0.093*	0.051	-0.006	0.839*
	(0.037)	(0.054)	(0.014)	(0.380)
Slope Change	0.309***	0.078	-0.006	-1.156**
	(0.072)	(0.080)	(0.013)	(0.383)
Constant	11.879***	9.118***	1.833***	77.090***
	(0.183)	(0.254)	(0.076)	(1.613)
Adj. R2	0.269	0.195	0.139	0.093
	Panel C: Intervention Year - 2014			
Level Change	0.104	0.008	-0.008	-0.441
	(0.059)	(0.157)	(0.041)	(1.165)
Pre-Trend	-0.006	0.135**	0.018*	0.959***
	(0.026)	(0.042)	(0.007)	(0.207)
Slope Change	0.218**	0.009	-0.024	-1.165**
	(0.064)	(0.057)	(0.015)	(0.339)
Constant	11.985***	9.363***	1.883***	78.213***
	(0.186)	(0.248)	(0.084)	(1.606)
Adj. R2	0.268	0.195	0.139	0.093

	Panel D: Intervention Year - 2015 (Actual Year of Tennessee Promise)			
Level Change	0.597**	0.433*	-0.058*	-0.292
	(0.160)	(0.195)	(0.025)	(0.800)
Pre-Trend	0.025	0.108**	0.015*	0.614*
	(0.020)	(0.037)	(0.007)	(0.263)
Slope Change	0.031	-0.106	-0.006	-0.938
	(0.040)	(0.065)	(0.017)	(0.519)
Constant	12.060***	9.407***	1.892***	78.135***
	(0.184)	(0.266)	(0.090)	(1.736)
Adj. R2	0.271	0.195	0.139	0.093
N	187,117	187,117	187,117	187,117

Note: Sample is the full (pooled) sample of both first-generation and non-first-generation students. Panels A, B, and C show estimates from models that presumed the intervention was implemented in 2012, 2013, or 2014, during which the Tennessee Transfer Pathways (TTP) program was being implemented, but the Tennessee Promise program was not. Panel D shows estimates with the intervention year as 2015, the year in which the Tennessee Promise was actually implemented. Models include controls for demographic characteristics, academic preparedness, financial resources, and institution and major fixed effects. Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001

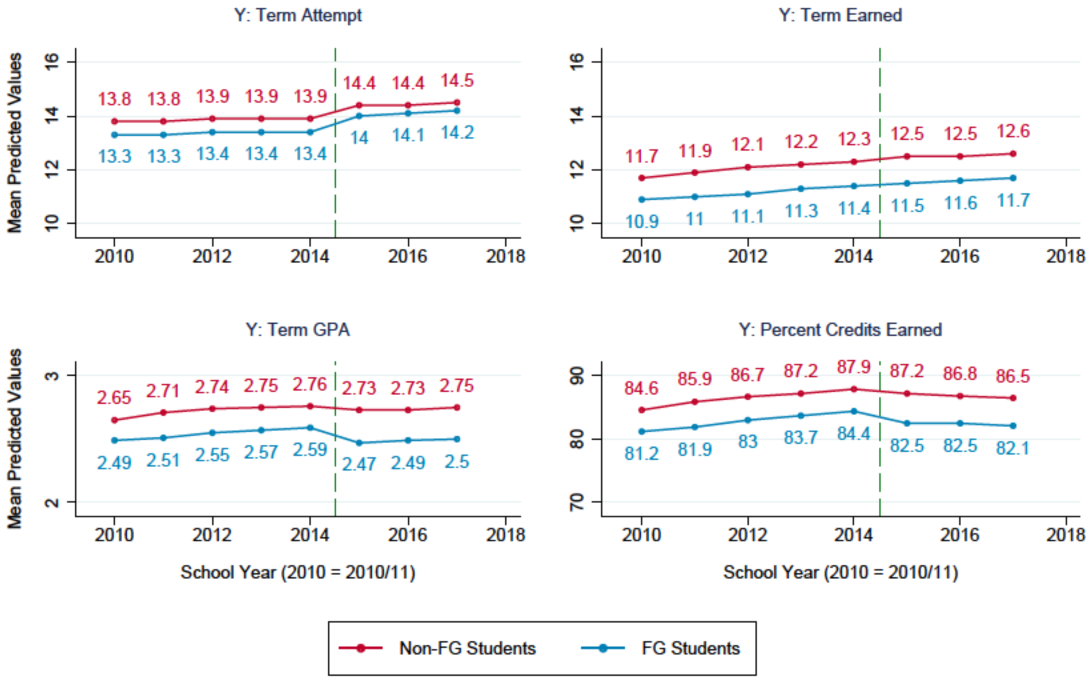
Table 3- 16 Estimates of First-Term Outcomes by First-Generation Status, Conservative Definition

	Panel A: Full Sample											
	Term Attempt			Term Earned			Term GPA			Percent Credits Earned		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	0.670***	0.558**	0.595**	0.376	0.458*	0.428*	-0.110**	-0.033	-0.059*	-1.073	0.080	-0.323
	(0.175)	(0.154)	(0.160)	(0.203)	(0.198)	(0.196)	(0.031)	(0.024)	(0.025)	(0.919)	(0.789)	(0.801)
Pre-Trend	0.015	0.031	0.025	0.096*	0.116*	0.109**	0.015*	0.015	0.015*	0.573**	0.642	0.618*
	(0.023)	(0.019)	(0.020)	(0.034)	(0.042)	(0.037)	(0.006)	(0.008)	(0.007)	(0.190)	(0.325)	(0.262)
Slope Change	0.066	0.010	0.031	-0.058	-0.140	-0.110	0.001	-0.011	-0.007	-0.757	-1.077	-0.961
	(0.047)	(0.037)	(0.040)	(0.064)	(0.070)	(0.065)	(0.018)	(0.017)	(0.017)	(0.469)	(0.578)	(0.515)
Constant	11.950***	12.071***	12.046***	9.077***	9.342***	9.308***	1.832***	1.843***	1.857***	76.071***	77.823***	77.501***
	(0.212)	(0.175)	(0.185)	(0.289)	(0.281)	(0.267)	(0.089)	(0.094)	(0.089)	(1.938)	(1.795)	(1.722)
Adj. R2	0.278	0.259	0.271	0.181	0.193	0.195	0.118	0.145	0.138	0.086	0.092	0.093
N	67,531	119,586	187,117	67,531	119,586	187,117	67,531	119,586	187,117	67,531	119,586	187,117

Panel B: Sample Excluding Tennessee Promise Students												
	Term Attempt			Term Earned			Term GPA			Percent Credits Earned		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	0.466**	0.346**	0.386**	0.171	0.176	0.176	-0.104*	-0.041	-0.061*	-1.390	-0.680	-0.904
	(0.157)	(0.108)	(0.122)	(0.198)	(0.168)	(0.172)	(0.038)	(0.030)	(0.029)	(0.979)	(0.896)	(0.868)
Pre-Trend	0.015	0.032	0.026	0.096*	0.116*	0.109**	0.014*	0.015	0.015*	0.570**	0.642	0.616*
	(0.023)	(0.018)	(0.020)	(0.034)	(0.042)	(0.037)	(0.006)	(0.008)	(0.006)	(0.189)	(0.324)	(0.262)
Slope Change	0.080	0.023	0.044	-0.027	-0.076	-0.058	0.007	-0.001	0.001	-0.613	-0.714	-0.681
	(0.054)	(0.046)	(0.047)	(0.079)	(0.072)	(0.070)	(0.020)	(0.017)	(0.018)	(0.534)	(0.621)	(0.565)
Constant	11.924***	12.077***	12.042***	9.017***	9.341***	9.281***	1.840***	1.855***	1.866***	75.654***	77.709***	77.241***
	(0.225)	(0.180)	(0.192)	(0.321)	(0.291)	(0.284)	(0.092)	(0.097)	(0.091)	(2.018)	(1.866)	(1.790)
Adj. R2	0.301	0.285	0.296	0.192	0.206	0.208	0.114	0.144	0.137	0.086	0.092	0.093
N	58,927	106,524	165,451	58,927	106,524	165,451	58,927	106,524	165,451	58,927	106,524	165,451

Note: Tables show estimates using a more conservative definition of first-generation student, specifically, students with no degree-holding parents. Students with at least one degree-holding parent are non-first-generation, along with students with two degree-holding parents. Models in Panel A present estimates using the full sample of students and models in Panel B present estimates using the sample excluding Tennessee Promise Students (TPS). Models include controls for demographic characteristics, academic preparedness, financial resources, and institution and major fixed effects. The first two columns within each outcome present estimates from subgroup models by first-generation status. The last column within each outcome present estimates using the pooled sample. Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Figure 3- 11 Linear Predictions of First-Term Outcomes by First-Generation Status, Conservative Definition



Note: Models display predicted values from subgroup models shown in Table 3-17, Panel A, for each outcome. Estimates calculated using a more conservative definition of first-generation student. Students with no degree-holding parents are first-generation and students with at least one degree-holding parent are non-first-generation. Model predictions aggregated by school-year and first-generation status. Models include controls for student demographic characteristics, academic preparedness, and access to financial resources, as well as institution and major fixed effects.

Table 3- 17 Estimated First-Term Outcomes, Categorical Definition of First-Generation Student

Panel A: Full Sample

	Term Attempted			Term Earned			Term GPA			Percent Credits Earned		
	FG - No Degree	FG - One Degree	Non-FG	FG - No Degree	FG - One Degree	Non-FG	FG - No Degree	FG - One Degree	Non-FG	FG - No Degree	FG - One Degree	Non-FG
Level Change	0.670***	0.631***	0.511**	0.376	0.598**	0.358	-0.110**	-0.028	-0.035	-1.076	0.647	-0.343
	(0.175)	(0.160)	(0.147)	(0.204)	(0.199)	(0.202)	(0.031)	(0.025)	(0.028)	(0.920)	(0.884)	(0.799)
Pre-Trend	0.015	0.019	0.040*	0.102**	0.098*	0.130*	0.016*	0.013*	0.018	0.616**	0.582	0.700
	(0.023)	(0.021)	(0.018)	(0.034)	(0.041)	(0.048)	(0.006)	(0.006)	(0.009)	(0.191)	(0.289)	(0.381)
Slope Change	0.066	0.033	-0.013	-0.065	-0.147	-0.131	-0.002	-0.016	-0.004	-0.813	-1.243*	-0.899
	(0.047)	(0.038)	(0.041)	(0.065)	(0.072)	(0.072)	(0.019)	(0.016)	(0.017)	(0.478)	(0.534)	(0.630)
Constant	11.99***	12.09***	12.22***	8.753***	8.86***	9.37***	1.69***	1.66***	1.72***	73.10***	73.56***	77.19***
	(0.242)	(0.219)	(0.209)	(0.308)	(0.274)	(0.313)	(0.086)	(0.095)	(0.082)	(2.032)	(1.982)	(1.848)
Adj. R2	0.278	0.261	0.251	0.179	0.186	0.189	0.113	0.132	0.141	0.083	0.090	0.085
N	67,531	53,805	65,781	67,531	53,805	65,781	67,531	53,805	65,781	67,531	53,805	65,781

Panel B: Sample Excluding Tennessee Promise Students

	Term Attempted			Term Earned			Term GPA			Percent Credits Earned		
	FG - No Degree	FG - One Degree	Non-FG	FG - No Degree	FG - One Degree	Non-FG	FG - No Degree	FG - One Degree	Non-FG	FG - No Degree	FG - One Degree	Non-FG
Level Change	0.468**	0.414**	0.302**	0.170	0.269	0.120	-0.106*	-0.052	-0.029	-1.413	-0.435	-0.810
	(0.157)	(0.131)	(0.089)	(0.200)	(0.181)	(0.167)	(0.038)	(0.037)	(0.030)	(0.981)	(0.954)	(0.923)
Pre-Trend	0.016	0.020	0.041*	0.102**	0.100*	0.131*	0.016*	0.012	0.018	0.617**	0.589	0.698
	(0.024)	(0.021)	(0.017)	(0.034)	(0.041)	(0.049)	(0.006)	(0.006)	(0.009)	(0.191)	(0.289)	(0.380)
Slope Change	0.080	0.053	-0.005	-0.034	-0.064	-0.086	0.005	-0.002	0.001	-0.662	-0.796	-0.634
	(0.054)	(0.042)	(0.051)	(0.079)	(0.083)	(0.068)	(0.021)	(0.018)	(0.017)	(0.538)	(0.594)	(0.653)
Constant	11.99***	12.10***	12.26***	8.70***	8.80***	9.40***	1.68***	1.65***	1.73***	72.56***	73.00***	77.08***
	(0.253)	(0.225)	(0.208)	(0.340)	(0.287)	(0.327)	(0.086)	(0.096)	(0.084)	(2.137)	(2.020)	(1.947)
Adj. R2	0.301	0.289	0.276	0.190	0.199	0.200	0.109	0.129	0.141	0.083	0.089	0.085
N	58,927	46,477	60,047	58,927	46,477	60,047	58,927	46,477	60,047	58,927	46,477	60,047

Note: Models present estimates of subgroup models predicting differences between first-generation students with no degree-holding parents or one degree-holding parent, and non-first-generation students with two degree-holding parents. Models in Panel A present estimates using the full sample of students and models in Panel B present estimates using the sample excluding Tennessee Promise Students (TPS). Within a given outcome, columns show estimates for the following subgroups: (1) first-generation students with no degree-holding parents, (2) first-generation students with exactly one degree-holding parent, and (3) non-first-generation students (two degree-holding parents). Models include controls for demographic characteristics, academic preparedness, financial resources, and institution and major fixed effects. Standard errors clustered by institution and are in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Appendix

Table A3- 1 Descriptive Statistics, Pre- and Post-Promise, by FAFSA Filing

	Panel A: FAFSA				**Panel B: No FAFSA**			
	Pre-Promise	Post-Promise	Difference	P-Value	Pre-Promise	Post-Promise	Difference	P-Value
Demographic Characteristics								
Male	43.24%	43.05%	0	0.073	54.62%	57.40%	0.03	0
Female	56.76%	56.95%	0	0.073	45.38%	42.60%	-0.03	0
White	72.81%	70.27%	-0.03	0	81.82%	78.37%	-0.03	0
Black	19.03%	18.33%	-0.01	0	9.42%	9.29%	0	0.476
Latinx	2.19%	3.86%	0.02	0	2.61%	4.67%	0.02	0
Asian	1.61%	1.82%	0	0	2.00%	2.38%	0	0
Other	4.37%	5.72%	0.01	0	4.15%	5.30%	0.01	0
Academic Preparedness								
ACT Composite	21.60	21.60	0	0.967	20.52	21.36	0.84	0
ACT Composite (Bottom 25%)	24.66%	25.69%	0.01	0	32.34%	25.00%	-0.07	0
ACT Composite (25-50%]	27.17%	26.65%	-0.01	0	30.65%	29.61%	-0.01	0.001
ACT Composite (50-75%]	23.19%	22.75%	0	0	20.73%	23.47%	0.03	0
ACT Composite (Top 25%)	24.98%	24.92%	0	0.529	16.28%	21.92%	0.06	0
Missing ACT Composite	5.18%	2.85%	-0.02	0	11.05%	6.74%	-0.04	0
Never Dual Enrolled	69.35%	62.66%	-0.07	0	74.55%	66.25%	-0.08	0
Dual Enrolled	30.65%	37.34%	0.07	0	25.45%	33.75%	0.08	0
N Observations	731,466	309,303			114,431	30,123		

Note: Table shows first-term difference in means for FAFSA filers (Panel A) and non-FAFSA filers (Panel B), pre- and post-Promise initiation. Columns 1 and 2 in each panel show covariate means pre- and post-Promise, respectively. Columns 3 and 4 in each panel show the difference and p-value from two-sided t-tests of mean equivalence. Students in the sample include students who are first-time, first-year students enrolled in Tennessee public two- or four-year colleges and universities (excluding Tennessee Career and Technical (TCAT) colleges), who are between ages 17 and 24 and are U.S. citizens and Tennessee residents.

Table A3- 2 Estimates of First-Term Outcomes by First-Generation Status, Conditioning Credits Earned by Credits Attempted

	Panel A: Full Sample					
	Term Earned (Unadjusted)			Term Earned (Adjusted)		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	0.481*	0.355	0.433*	-0.020	-0.068	-0.035
	(0.197)	(0.201)	(0.195)	(0.113)	(0.125)	(0.111)
Pre-Trend	0.097**	0.126*	0.108**	0.084*	0.093	0.088*
	(0.034)	(0.046)	(0.037)	(0.031)	(0.054)	(0.038)
Slope Change	-0.097	-0.124	-0.106	-0.136	-0.112	-0.131
	(0.065)	(0.070)	(0.065)	(0.066)	(0.086)	(0.072)
Constant	9.097***	9.611***	9.407***	-0.080	-0.365	-0.061
	(0.265)	(0.319)	(0.266)	(0.410)	(0.623)	(0.464)
Adj. R2	0.185	0.190	0.195	0.310	0.347	0.329
N	121,336	65,781	187,117	121,336	65,781	187,117

	Panel B: Sample Excluding Tennessee Promise Students					
	Term Earned (Unadjusted)			Term Earned (Adjusted)		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	0.223	0.120	0.182	-0.119	-0.132	-0.125
	(0.182)	(0.168)	(0.171)	(0.120)	(0.141)	(0.122)
Pre-Trend	0.098**	0.127*	0.109**	0.084*	0.093	0.088*
	(0.034)	(0.047)	(0.037)	(0.031)	(0.054)	(0.038)
Slope Change	-0.044	-0.080	-0.055	-0.096	-0.076	-0.090
	(0.077)	(0.067)	(0.071)	(0.074)	(0.089)	(0.079)
Constant	9.048***	9.628***	9.379***	-0.209	-0.467	-0.185
	(0.282)	(0.334)	(0.282)	(0.406)	(0.620)	(0.464)
Adj. R2	0.197	0.200	0.208	0.328	0.361	0.346
N	105,404	60,047	165,451	105,404	60,047	165,451

Note: Table compares estimates of differences in credits earned from the original model in Table 3-10 with estimates of differences in credits earned after adjusting for credits attempted. Conditional on credits attempted, differences in term credits earned are null. Models in Panel A present estimates using the full sample of students and models in Panel B present estimates using the sample excluding Tennessee Promise Students. Models include controls for demographic characteristics, academic preparedness, financial resources, major, and institution fixed effects. The first two columns within each outcome present estimates from subgroup models by first-generation status. The last column in each panel shows results from a pooled model. Standard errors clustered by institution and are in parentheses.
* p<0.05 **p<0.01 ***p<0.001.

Table A3- 3 Estimates of First-Term Outcomes by First-Generation Status and Institution Type, Conditioning Credits Earned by Credits Attempted

	Panel A: Full Sample											
	Term Earned (Unadjusted)						Term Earned (Adjusted)					
	Community College			4-Year			Community College			4-Year		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	0.880**	0.906**	0.891**	0.032	-0.015	0.009	0.177	0.165	0.197	-0.738	-0.803	-0.764
	-0.265	-0.252	-0.258	-0.163	-0.165	-0.157	-1.304	-1.301	-1.259	-0.96	-1.015	-0.936
Pre-Trend	0.021	0.099*	0.043	0.164*	0.136	0.153*	0.366*	0.772**	0.481**	0.744	0.589	0.681
	-0.031	-0.04	-0.033	-0.054	-0.073	-0.062	-0.138	-0.202	-0.151	-0.395	-0.547	-0.461
Slope Change	-0.05	-0.144	-0.078	-0.133	-0.104	-0.119	-0.945	-1.309*	-1.059	-0.875	-0.517	-0.728
	-0.084	-0.101	-0.086	-0.097	-0.093	-0.095	-0.579	-0.586	-0.564	-0.763	-0.87	-0.823
Constant	7.633***	8.316***	8.074***	9.096***	9.817***	9.682***	77.853***	81.246***	76.016***	75.685***	81.315***	78.347***
	-0.273	-0.336	-0.327	-0.489	-0.561	-0.438	-2.086	-1.848	-2.088	-3.691	-3.729	-2.999
Adj. R2	0.153	0.164	0.158	0.098	0.094	0.102	0.086	0.079	0.086	0.074	0.073	0.078
	63,900	23,569	87,469	57,436	42,212	99,648	63,900	23,569	87,469	57,436	42,212	99,648

Panel B: Sample Excluding Tennessee Promise Students

	Term Earned (Unadjusted)						Term Earned (Adjusted)					
	Community College			4-Year			Community College			4-Year		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	0.880**	0.906**	0.891**	0.032	-0.015	0.009	0.177	0.165	0.197	-0.738	-0.803	-0.764
	-0.265	-0.252	-0.258	-0.163	-0.165	-0.157	-1.304	-1.301	-1.259	-0.96	-1.015	-0.936
Pre-Trend	0.021	0.099*	0.043	0.164*	0.136	0.153*	0.366*	0.772**	0.481**	0.744	0.589	0.681
	-0.031	-0.04	-0.033	-0.054	-0.073	-0.062	-0.138	-0.202	-0.151	-0.395	-0.547	-0.461
Slope Change	-0.05	-0.144	-0.078	-0.133	-0.104	-0.119	-0.945	-1.309*	-1.059	-0.875	-0.517	-0.728
	-0.084	-0.101	-0.086	-0.097	-0.093	-0.095	-0.579	-0.586	-0.564	-0.763	-0.87	-0.823
Constant	7.633***	8.316***	8.074***	9.096***	9.817***	9.682***	77.853***	81.246***	76.016***	75.685***	81.315***	78.347***
	-0.273	-0.336	-0.327	-0.489	-0.561	-0.438	-2.086	-1.848	-2.088	-3.691	-3.729	-2.999
Adj. R2	0.153	0.164	0.158	0.098	0.094	0.102	0.086	0.079	0.086	0.074	0.073	0.078
	63,900	23,569	87,469	57,436	42,212	99,648	63,900	23,569	87,469	57,436	42,212	99,648

Note: Table compares estimates of differences in credits earned from the original model in Table 3-13 with estimates of differences in credits earned after adjusting for credits attempted. Conditional on credits attempted, differences in term credits earned are null. Models present estimates using the full sample of students. Within a given outcome, columns show the following models: (1) Non-FG in CC, (2) Non-FG in a 4-year, (3) FG in a CC, and (4) FG in a 4-year. Models include controls for demographic characteristics, academic preparedness, financial resources, major, and institution fixed effects within institution type. Since subgroup models are estimated, institution fixed effects include dummy variables for individual institutions attended within each institution type. Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Table A3- 4 Estimates of First-Term Outcomes by First-Generation Status, Huber-White Robust Standard Errors

	Panel A: Full Sample											
	Term Attempt			Term Earned			Term GPA			Percent Credits Earned		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	0.654***	0.512***	0.597***	0.481***	0.355***	0.433***	-0.072***	-0.037*	-0.058***	-0.273	-0.375	-0.292
	(0.025)	(0.034)	(0.020)	(0.050)	(0.065)	(0.040)	(0.013)	(0.018)	(0.011)	(0.334)	(0.419)	(0.262)
Pre-Trend	0.017***	0.040***	0.025***	0.097***	0.126***	0.108***	0.014***	0.017***	0.015***	0.579***	0.668***	0.614***
	(0.005)	(0.006)	(0.004)	(0.010)	(0.012)	(0.007)	(0.003)	(0.003)	(0.002)	(0.065)	(0.077)	(0.050)
Slope Change	0.051***	-0.014	0.031***	-0.097***	-0.124***	-0.106***	-0.006	-0.001	-0.006	-0.967***	-0.842***	-0.938***
	(0.011)	(0.015)	(0.009)	(0.023)	(0.031)	(0.018)	(0.006)	(0.008)	(0.005)	(0.151)	(0.197)	(0.121)
Constant	11.986***	12.097***	12.060***	9.097***	9.611***	9.407***	1.829***	1.889***	1.892***	76.144***	79.906***	78.135***
	(0.051)	(0.071)	(0.042)	(0.099)	(0.131)	(0.080)	(0.027)	(0.035)	(0.022)	(0.665)	(0.841)	(0.528)
Adj. R2	0.273	0.251	0.271	0.185	0.190	0.195	0.126	0.144	0.139	0.089	0.087	0.093
N	121,336	65,781	187,117	121,336	65,781	187,117	121,336	65,781	187,117	121,336	65,781	187,117

Panel B: Sample Excluding Tennessee Promise Students

	Term Attempt			Term Earned			Term GPA			Percent Credits Earned		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	0.443***	0.303***	0.387***	0.223***	0.120	0.182***	-0.078***	-0.030	-0.059***	-0.901*	-0.815	-0.872**
	(0.031)	(0.039)	(0.024)	(0.062)	(0.075)	(0.048)	(0.017)	(0.020)	(0.013)	(0.414)	(0.480)	(0.317)
Pre-Trend	0.017***	0.041***	0.026***	0.098***	0.127***	0.109***	0.014***	0.016***	0.015***	0.578***	0.666***	0.612***
	(0.005)	(0.006)	(0.004)	(0.010)	(0.012)	(0.007)	(0.003)	(0.003)	(0.002)	(0.065)	(0.077)	(0.050)
Slope Change	0.068***	-0.006	0.044***	-0.044	-0.080*	-0.055*	0.003	0.003	0.003	-0.695***	-0.590**	-0.659***
	(0.014)	(0.018)	(0.011)	(0.029)	(0.036)	(0.023)	(0.008)	(0.010)	(0.006)	(0.192)	(0.227)	(0.148)
Constant	11.967***	12.118***	12.053***	9.048***	9.628***	9.379***	1.836***	1.904***	1.901***	75.791***	79.850***	77.895***
	(0.055)	(0.074)	(0.044)	(0.105)	(0.135)	(0.084)	(0.028)	(0.036)	(0.023)	(0.703)	(0.867)	(0.552)
Adj. R2	0.298	0.276	0.296	0.197	0.200	0.208	0.123	0.145	0.138	0.088	0.087	0.093
N	105,404	60,047	165,451	105,404	60,047	165,451	105,404	60,047	165,451	105,404	60,047	165,451

Note: Models in Panel A present estimates using the full sample of students and models in Panel B present estimates using the sample excluding Tennessee Promise Students. Models include controls for demographic characteristics, academic preparedness, financial resources, major, and institution fixed effects. The first two columns within each outcome present estimates from subgroup models by first-generation status. The last column within each outcome presents estimates from the pooled sample. Robust standard errors in parentheses. * p<0.05 **p<0.01 ***p<0.001.

Table A3- 5 Estimates of First-Term Outcomes by First-Generation Status and Institution Type, Huber-White Standard Errors

	Panel A											
	Term Attempted						Term Earned					
	Community College			4-Year			Community College			4-Year		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	1.077***	1.093***	1.080***	0.164***	0.127***	0.144***	0.880***	0.906***	0.891***	0.032	-0.015	0.009
	(0.037)	(0.063)	(0.032)	(0.030)	(0.036)	(0.023)	(0.068)	(0.109)	(0.058)	(0.073)	(0.079)	(0.054)
Pre-Trend	-0.041***	-0.001	-0.030***	0.072***	0.060***	0.067***	0.021	0.099***	0.043***	0.164***	0.136***	0.153***
	(0.008)	(0.015)	(0.007)	(0.006)	(0.006)	(0.004)	(0.014)	(0.022)	(0.012)	(0.013)	(0.014)	(0.010)
Slope Change	0.109***	0.026	0.086***	-0.011	-0.035*	-0.019	-0.050	-0.144**	-0.078**	-0.133***	-0.104**	-0.119***
	(0.016)	(0.029)	(0.014)	(0.013)	(0.016)	(0.010)	(0.031)	(0.051)	(0.026)	(0.033)	(0.037)	(0.025)
Constant	9.857***	10.255***	10.763***	12.262***	12.213***	12.528***	7.633***	8.316***	8.074***	9.096***	9.817***	9.682***
	(0.076)	(0.128)	(0.067)	(0.063)	(0.078)	(0.047)	(0.128)	(0.203)	(0.113)	(0.152)	(0.171)	(0.105)
Adj. R2	0.184	0.183	0.184	0.104	0.083	0.096	0.153	0.164	0.158	0.098	0.094	0.102

Panel B

	Term GPA						Percent Credits Earned					
	Community College			4-Year			Community College			4-Year		
	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample	FG	Non-FG	Full Sample
Level Change	-0.125***	-0.109***	-0.119***	0.004	0.010	0.007	0.177	0.165	0.197	-0.738	-0.803	-0.764*
	(0.018)	(0.030)	(0.016)	(0.019)	(0.021)	(0.014)	(0.470)	(0.722)	(0.394)	(0.465)	(0.499)	(0.342)
Pre-Trend	0.013***	0.030***	0.018***	0.012***	0.008*	0.011***	0.366***	0.772***	0.481***	0.744***	0.589***	0.681***
	(0.004)	(0.006)	(0.003)	(0.003)	(0.004)	(0.003)	(0.099)	(0.151)	(0.083)	(0.085)	(0.088)	(0.062)
Slope Change	-0.010	-0.022	-0.014	-0.004	0.009	0.001	-0.945***	-1.309***	-1.059***	-0.875***	-0.517*	-0.728***
	(0.008)	(0.014)	(0.007)	(0.009)	(0.010)	(0.007)	(0.213)	(0.342)	(0.181)	(0.212)	(0.233)	(0.158)
Constant	1.969***	2.033***	1.910***	1.493***	1.698***	1.701***	77.853***	81.246***	76.016***	75.685***	81.315***	78.347***
	(0.035)	(0.055)	(0.031)	(0.040)	(0.045)	(0.028)	(0.897)	(1.372)	(0.780)	(0.983)	(1.091)	(0.675)
Adj. R2	0.115	0.111	0.117	0.130	0.150	0.145	0.086	0.079	0.086	0.074	0.073	0.078
N	63,900	23,569	87,469	57,436	42,212	99,648	63,900	23,569	87,469	57,436	42,212	99,648

Note: Models present estimates using the full sample of students. Within a given outcome, columns show the following models: (1) Non-FG in CC, (2) Non-FG in a 4-year, (3) FG in a CC, and (4) FG in a 4-year. Models include controls for demographic characteristics, academic preparedness, financial resources, major, and institution fixed effects within institution type. Since subgroup models are estimated, institution fixed effects include dummy variables for individual institutions attended within each institution type. The first two columns within each outcome present estimates from subgroup models by first-generation status. The last column within each outcome presents estimates from the pooled sample. Robust standard errors in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Table A3- 6 Tests for Alternate Treatment in Years Before Promise (2012-2014), First-Generation Students

	Panel A: Treatment Year - 2012			
	Term Attempted	Term Earned	Term GPA	Percent Credits Earned
Level Change	-0.368**	0.000	0.035	2.034**
	(0.098)	(0.093)	(0.017)	(0.582)
Slope Pre	-0.103	-0.015	-0.007	0.457
	(0.070)	(0.052)	(0.016)	(0.331)
Slope Change	0.336**	0.172*	0.000	-0.669
	(0.092)	(0.077)	(0.019)	(0.403)
Constant	11.929***	8.758***	1.779***	74.120***
	(0.178)	(0.252)	(0.088)	(1.831)
Adj. R2	0.271	0.184	0.125	0.089
	Panel B: Treatment Year - 2013			
Level Change	-0.026	0.156	0.082*	1.279
	(0.074)	(0.094)	(0.035)	(0.746)
Pre-Trend	-0.113*	0.037	-0.009	0.863*
	(0.040)	(0.056)	(0.012)	(0.370)
Slope Change	0.350***	0.100	-0.009	-1.232**
	(0.074)	(0.077)	(0.013)	(0.381)
Constant	11.809***	8.829***	1.769***	75.245***
	(0.199)	(0.262)	(0.084)	(1.747)
Adj. R2	0.271	0.184	0.126	0.089
	Panel C: Treatment Year - 2014			
Level Change	0.119	0.024	-0.009	-0.485
	(0.064)	(0.134)	(0.035)	(1.003)
Pre-Trend	-0.020	0.121**	0.017*	0.947***
	(0.028)	(0.042)	(0.007)	(0.202)
Slope Change	0.252***	0.028	-0.028	-1.209***
	(0.062)	(0.060)	(0.015)	(0.316)
Constant	11.910***	9.060***	1.820***	76.311***
	(0.200)	(0.255)	(0.089)	(1.736)
Adj. R2	0.270	0.184	0.125	0.089

	Panel D: Treatment Year - 2015 (Actual Year of Tennessee Promise)			
Level Change	0.654***	0.481*	-0.072*	-0.273
	(0.166)	(0.197)	(0.027)	(0.864)
Pre-Trend	0.017	0.097**	0.014*	0.579*
	(0.022)	(0.034)	(0.005)	(0.213)
Slope Change	0.051	-0.097	-0.006	-0.967
	(0.041)	(0.065)	(0.017)	(0.479)
Constant	11.986***	9.097***	1.829***	76.144***
	(0.199)	(0.265)	(0.092)	(1.810)
Adj. R2	0.273	0.185	0.126	0.089
N	121,336	121,336	121,336	121,336

Note: Table shows results of alternate treatment years for the first-generation students. Panels A, B, and C show estimates from models that presumed the intervention was implemented in 2012, 2013, or 2014, during which the Tennessee Transfer Pathways (TTP) program was being implemented, but the Tennessee Promise program was not. Panel D shows estimates with the intervention year as 2015, the year in which the Tennessee Promise was actually implemented for the first time. Results in Panel D are equivalent to those in the first-generation subgroup columns in Table 3-10. Models include controls for demographic characteristics, academic preparedness, financial resources, major, and institution fixed effects. Standard errors clustered by institution and are in parentheses.
* $p<0.05$ **$p<0.01$ ***$p<0.001$

Table A3- 7 Tests for Alternate Treatment in Years Before Promise (2012-2014) Non-First-Generation Students

	Term Attempted	Term Earned	Term GPA	Percent Credits Earned
	Panel A: Treatment Year - 2012			
Level Change	-0.229*	0.019	-0.014	1.434*
	(0.093)	(0.101)	(0.023)	(0.679)
Slope Pre	-0.061	0.077	0.037	0.835*
	(0.048)	(0.067)	(0.023)	(0.339)
Slope Change	0.239**	0.066	-0.028	-0.845
	(0.075)	(0.118)	(0.025)	(0.477)
Constant	11.966***	9.218***	1.855***	77.861***
	(0.156)	(0.311)	(0.075)	(2.016)
Adj. R2	0.250	0.189	0.144	0.087
	Panel B: Treatment Year - 2013			
Level Change	0.015	0.194	0.054	1.370
	(0.085)	(0.111)	(0.049)	(0.902)
Pre-Trend	-0.059	0.073	-0.000	0.802
	(0.036)	(0.054)	(0.018)	(0.426)
Slope Change	0.235**	0.041	-0.000	-1.016*
	(0.073)	(0.095)	(0.019)	(0.432)
Constant	11.908***	9.291***	1.832***	78.665***
	(0.171)	(0.288)	(0.071)	(1.657)
Adj. R2	0.250	0.189	0.145	0.087
	Panel C: Treatment Year - 2014			
Level Change	0.104	-0.009	-0.015	-0.438
	(0.072)	(0.190)	(0.057)	(1.515)
Pre-Trend	0.015	0.157**	0.021*	0.981***
	(0.023)	(0.044)	(0.009)	(0.244)
Slope Change	0.152*	-0.025	-0.014	-1.065*
	(0.070)	(0.057)	(0.016)	(0.393)
Constant	12.015***	9.554***	1.880***	79.886***
	(0.181)	(0.284)	(0.082)	(1.666)
Adj. R2	0.250	0.189	0.144	0.087

	Panel D: Treatment Year - 2015 (Actual Year of Tennessee Promise)			
Level Change	0.512**	0.355	-0.037	-0.375
	(0.147)	(0.201)	(0.029)	(0.803)
Pre-Trend	0.040*	0.126*	0.017	0.668
	(0.018)	(0.046)	(0.009)	(0.368)
Slope Change	-0.014	-0.124	-0.001	-0.842
	(0.041)	(0.070)	(0.017)	(0.617)
Constant	12.097***	9.611***	1.889***	79.906***
	(0.174)	(0.319)	(0.095)	(1.957)
Adj. R2	0.251	0.190	0.144	0.087
N	121,336	121,336	121,336	121,336

Note: Table shows results of alternate treatment years for the non-first-generation students. Panels A, B, and C show estimates from models that presumed the intervention was implemented in 2012, 2013, or 2014, during which the Tennessee Transfer Pathways (TTP) program was being implemented, but the Tennessee Promise program was not. Panel D shows estimates with the intervention year as 2015, the year in which the Tennessee Promise was actually implemented for the first time. Results in Panel D are equivalent to those in the non-first-generation subgroup columns in Table 3-10. Models include controls for demographic characteristics, academic preparedness, financial resources, major, and institution fixed effects. Standard errors clustered by institution and are in parentheses. * p<0.05 **p<0.01 ***p<0.001

Table A3- 8 Descriptive Statistics of Outcomes by Cohort, Pre- and Post-Promise

	Pre-Promise					Post-Promise		
Predictor Variables	2010	2011	2012	2013	2014	2015	2016	2017
Outcomes								
Credits Attempted in First Term	13.58	13.51	13.45	13.67	13.70	14.10	14.15	14.28
Credits Earned in First Term	11.19	11.27	11.45	11.81	11.68	11.89	11.97	11.93
Percent Credits Earned in First Term	82.17%	83.10%	84.67%	85.95%	84.96%	84.18%	84.48%	83.36%
GPA in First Term	2.55	2.59	2.59	2.68	2.64	2.57	2.59	2.58
N Observations	22,096	22,778	22,820	23,314	22,512	24,279	24,151	25,167

Note: Table shows first-term difference in means across cohorts for all outcomes in the main analytic sample. Cohort membership determined based on the school year in which a student first enrolled. For instance, a student enrolling for the first time in the fall of 2010 or in the spring of 2011 would be considered a part of the 2010/11 cohort. First-time, first-year students who enrolled in college between 2010-2014 enrolled prior to the start of TN Promise and would not have been eligible to apply for the Promise. First-time, first-year students who enrolled in college between the 2015-2017 school years would have been eligible for the TN Promise when they were high school seniors.

Chapter 5

Conclusion

This dissertation aims to examine ways in which students from historically marginalized backgrounds—namely, English Learners, and first-generation college students—access types of capital and how access may aid in their academic achievement. Findings from these studies demonstrate how students from historically marginalized backgrounds may benefit from greater access to capital. For ELs, assignment to a highly effective reading teacher, as measured by the teachers' value-added, observation, or overall level of effectiveness score, creates improved opportunity for learning the English language. For first-generation students, access to greater levels of parental capital around college-going is associated with improved first-term outcomes, as is greater access to financial, social, and cultural capital through the Tennessee Promise program.

However, the analyses also reveal stark gaps in students' access to capital. Study one finds that, compared to ELs who score below basic in reading proficiency, ELs who score basic proficient, proficient, or advanced proficient are significantly more likely to be assigned to a highly effective classroom reading teacher, indicating systematic, disproportionately lower access to effective teachers for low performing ELs. Findings from studies two and three show that first-generation students are more likely to be students of color, have fewer financial resources, be less academic prepared for college, and are less likely to enroll in a four-year institution. These findings emphasize that gaps in capital are prevalent, significant barriers to accessing educational opportunities.

Findings from these studies denote that capital is built iteratively and through interpersonal interactions. While not directly measured in these studies, the mechanism through which students experienced improvements—whether it is through assignment to an effective teacher, or exposure to information and resources through a Promise program—consist of daily interactions with people and programs that support students' understanding. To this end, policy seeking to bridge gaps in students' access to capital should keep in mind that the development of capital is an ongoing, iterative, and deeply social process. As documented in the chapters above, students from marginalized backgrounds benefit academically when they have access to a system of social structures that creates opportunities for students to access capital. It is notable that study two finds little heterogeneity in first-generation outcomes based on financial resources and that study three observes improved outcomes for students who do not receive Promise funding. These findings speak to the importance of receiving supports other than financial resources, such as information, guidance, and other forms of social and cultural capital. Policies that create lasting opportunities for students to access capital through long-term pairing with a teacher, a series of workshops or mentorship, or a long-lasting program, may be well-suited to build students' long-term capacity to access educational opportunities.

Accordingly, future work may consider documenting how capital is disseminated, accessed, and experienced by students on a day to day basis. For ELs, this could be an examination of the practices and approaches effective mainstream classroom teachers use to instruct ELs. For first-generation students, studies can examine the role of counselors, siblings, and other mentors in developing students' college-going capital, and the types of information transmitted during their interactions. Additionally, promise programs offer a potential solution for states and localities to offer information and financial resources at scale. Qualitative analyses can examine how promise programs are implemented, how they are experienced, what information students find most useful, and fidelity of program implementation.