Annenberg Institute
BROWN UNIVERSITY

EdWorkingPaper No. 25-1167

Get a Skill, Get a Job, Get Ahead? Evaluating the Effects of Virginia's Workforce-Targeted Free College Program

Sade Bonilla
University of Pennsylvania

Daniel Sparks
University of Arkansas

Tuition-free college programs are gaining momentum as policymakers address rising college costs and workforce readiness. Despite their growing adoption, limited research examines how workforce-focused eligibility criteria impact student outcomes beyond enrollment. This pre-registered study employs two within-study quasi-experimental designs—differencein- discontinuity and difference-in-differences— to estimate the causal impact of Virginia's Get a Skill, Get a Job, Get Ahead (G3) initiative on financial aid and academic outcomes for community college students. Launched as a pandemic recovery effort, G3 aimed to reverse enrollment declines and address labor shortages by leveraging simplified 'free college' messaging and offering last-dollar scholarships and additional advising support for students in high-demand workforce programs. We find that G3 significantly increased FAFSA completion, total financial aid, and grant aid, with gains concentrated among middle-income students. The program also reduced student borrowing, consistent with crowd-out by grant aid. Certificate completion rose by 5.1 to 6.6 percentage points, and higher enrollment translated these gains into a net increase in the number of students earning certificates in targeted fields. These findings suggest workforce-targeted tuition-free programs can expand financial aid access, increase the supply of certified workers in priority fields, and better align higher education with workforce demands.

VERSION: October 2025

Suggested citation: Bonilla, Sade, and Daniel Sparks. (2025). Get a Skill, Get a Job, Get Ahead? Evaluating the Effects of Virginia's Workforce-Targeted Free College Program. (EdWorkingPaper: 25 -1167). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/q32w-tw61

Get a Skill, Get a Job, Get Ahead? Evaluating the Effects of Virginia's Workforce-Targeted Free College Program

Sade Bonilla [1] Daniel Sparks [2] *

October 1, 2025

Abstract

Tuition-free college programs are gaining momentum as policymakers address rising college costs and workforce readiness. Despite their growing adoption, limited research examines how workforce-focused eligibility criteria impact student outcomes beyond enrollment. This pre-registered study employs two within-study quasi-experimental designs—difference-in-discontinuity and difference-in-differences— to estimate the causal impact of Virginia's Get a Skill, Get a Job, Get Ahead (G3) initiative on financial aid and academic outcomes for community college students. Launched as a pandemic recovery effort, G3 aimed to reverse enrollment declines and address labor shortages by leveraging simplified 'free college' messaging and offering last-dollar scholarships and additional advising support for students in high-demand workforce programs. We find that G3 significantly increased FAFSA completion, total financial aid, and grant aid, with gains concentrated among middle-income students. The program also reduced student borrowing, consistent with crowd-out by grant aid. Certificate completion rose by 5.1 to 6.6 percentage points, and higher enrollment translated these gains into a net increase in the number of students earning certificates in targeted fields. These findings suggest workforce-targeted tuition-free programs can expand financial aid access, increase the supply of certified workers in priority fields, and better align higher education with workforce demands.

JEL No. I23, I22, J24

Keywords: tuition-free college, workforce development, community college outcomes, financial aid policy

*1. University of Pennsylvania sadeb@upenn.edu (corresponding author) 2. University of Arkansas, ds197@uark.edu. We thank seminar participants at AEFP, APPAM, CSCC, the ARCC Network, and Boston University for their helpful feedback. We are grateful to Catherine Finnegan, Marina Bagreev, Laurie Owens, Aris Bearse, Angela Lawhorne and Carrie Owens of the Virginia Community College System for providing data access, answering our questions, and discussing the implementation of the G3 program; this research would not have been possible without their deep collaboration. We also thank Patrick Lavallee Delgado for his excellent research assistance. This study was supported by grant R305X220024 from the Institute of Education Sciences (IES) from September 1, 2022, to March 7, 2025. The content and views are solely the responsibility of the authors and do not necessarily reflect the views of IES.

1 Introduction

Rising college costs and structural barriers— such as financial aid and application complexities, inadequate academic preparation, and challenges selecting and persisting through a program—pose significant obstacles to increasing educational attainment, particularly for students who enroll in community college (Scott-Clayton, 2015; Dynarski, Page, & Scott-Clayton, 2023; Dynarski et al., 2023). These challenges are especially pronounced for students from low-income backgrounds, first-generation college students, and adult learners returning to school. Key economic trends, such as technological advancements, automation, and the rise of the gig economy are reshaping labor demands, making it increasingly important for community colleges to prepare students adequately (Stanford, 2017; Acemoglu & Restrepo, 2019). In response, tuition-free college programs have emerged as a promising approach to address these barriers by improving affordability and aligning educational programs with the demands of a rapidly changing labor market. However, a fundamental challenge in evaluating the causal effects of such programs lies in their substantial impact on student enrollment behavior (Gurantz, 2020; House & Dell, 2020; Nguyen, 2020). Because these initiatives can dramatically reshape who enrolls, they induce compositional shifts that obscure downstream effects on academic and labor market outcomes. This selection bias complicates causal inference, making it difficult to isolate program effects from changes in the student population.

Existing research on tuition-free programs has focused largely on early enrollment effects, with more limited findings on completion rates (Gurantz, 2020; House & Dell, 2020; Nguyen, 2020). The findings on completion rates remain mixed, likely due to differences in program eligibility requirements, varied funding structures, and levels of student support. Virginia's Get a Skill, Get a Job, Get Ahead (G3) initiative, launched in 2021, provides a unique opportunity to overcome some of these challenges and rigorously assess the causal effects of a workforce-oriented tuition-free program. G3's design, which prioritizes workforce needs, includes both first- and last-dollar grant aid components, and to a lesser extent, advising supports, prioritizing students pursuing career-aligned credentials.

Critically, the program's eligibility structure allows for two complementary quasi-experimental approaches. First, G3's income-based eligibility threshold enables a difference-in-discontinuity (RD-DD) design, which builds on the local validity of a regression discontinuity by differencing out threshold effects observed among non-treatment students in ineligible programs and in pre-policy cohorts. This approach provides internally valid estimates of causal effects at the income eligibility threshold by isolating policy-induced discontinuities from other shocks occurring at the same cutoff. Second, because only certain academic programs qualified for G3 funding, we leverage this variation in a differences-in-differences (DID) framework, comparing outcomes for students in eligible and ineligible programs before and after the policy's introduction. While the RD-DD offers highly credibly causal estimates, they are local to students near the income cutoff. The DID provides a broader view by capturing changes in the composition of students served and offers bounds on whether the RD-DD estimates may generalize. By leveraging both income-based thresholds and academic program-level eligibility, our study provides new insights into how workforce-aligned tuition-free programs impact financial aid, enrollment behavior, and educational attainment.

Workforce-focused tuition subsidies are increasingly popular across the United States, reflecting broad political appeal and the role community colleges play in workforce preparation. However, labor market shifts have expanded both low- and high-wage jobs while reducing middle-skill opportunities, and programs like G3 may provide an immediate pathway for students to access stable, middle-skill employment (Autor, 2014; Deming, 2017; Goos, Manning & Salomons, 2014). Whether such programs improve educational attainment and financial aid access without unintentionally tracking students into lower-return pathways remains an open question. By examining G3's impact on financial aid, enrollment behavior, and early academic attainment, this study contributes to the broader debate on the role of workforce-focused interventions in postsecondary education policy.

In this study, we provide quasi-experimental evidence of G3's early impacts on students' financial aid and academic outcomes using complementary RD-DD and DID estimation strategies. Specifically, this pre-registered study evaluates the program's effects on three confirmatory outcomes: FAFSA completion, total financial aid received, and early measures of degree completion.

We find that the G3 initiative significantly increased FAFSA completion rates and total financial aid received, driven primarily by an increase in grant aid— a result confirmed by both estimation approaches. RD-DD estimates at the income eligibility cutoff show meaningful increases in degree and credential completion, corresponding with findings from DID estimates capturing growth in certificate completion for the broader population of community college students. Together, these findings suggest that workforce-targeted tuition-free programs can expand financial aid access, reduce borrowing, increase the supply of certified workers, and support state efforts to align higher education with labor market needs.

2 Background

2.1 Get a Skill, Get a Job, Get Ahead

The G3 initiative emerged from a bipartisan effort to promote workforce education at community colleges in response to a rapidly evolving economy. Proposed in 2019 and enacted in 2021 as part of the state's pandemic recovery strategy, G3 aimed to address workforce shortages in high-demand sectors while recovering enrollment losses—which dropped by over 7 percent between 2019 and 2021. Unlike broad tuition-free programs, G3 is restricted to workforce programs in five key areas: health care, information technology and computer science, manufacturing and skilled trades, early childhood education, and public safety. Program eligibility is determined by the Virginia Office of Education Economics (VOEE), which evaluates current and projected job availability in various regions.[1]

Over its first three years, the program invested $45 million to strengthen connections between education and the labor market by providing direct student aid. A defining feature of G3 is its last-dollar scholarship, which covers tuition for community college students with incomes up to 400 percent of the federal poverty level (FPL), adjusting for family size. As of 2022, over 50 percent of Virginians fell within this income threshold, indicating broad program accessibility. In addition to tuition support, the state allocated $5 million for hiring 60 additional advisors to reduce in-

[1]For the 2023-24 school year health and hospitality programs were added to the list of eligible programs, however, this study examines the early implementation period and only includes the five stated program areas.

formation barriers for current and prospective students by providing holistic support services.[2] These advisors assisted students in identifying eligible programs and navigating the application and financial aid process. Additionally, advisors provided support in program selection and requirement completion.

Ultimately this small portion of G3 funding—10 percent— provided colleges with 60 additional staff to boost take up of the workforce-targeted free college program. Prior research has highlighted low FAFSA completion rates among lower-income families due to lack of awareness and program complexity (Bettinger et al., 2012; Bhargava & Manoli, 2015). Recognizing this challenge, G3 advisors provided potential students with information and assistance in selecting a program, applying and enrolling, and filing a FAFSA. Because the FAFSA is a requirement for receiving G3 aid in credit-bearing programs, efforts to increase FAFSA completion were critical to the program's success. However, communicating the complexity of the financial aid process remained a challenge for college advisors. A qualitative implementation study found that advisors scaled back "free college" messaging due to uncertainty about whether applicants would ultimately qualify (Cormier et al., 2024).

To further reduce information gaps, the VCCS developed G3 marketing materials and a toolkit for adaptation by the state's 23 community colleges. This effort emphasized simplified messaging that highlighted the five eligible program areas and high-demand for related jobs through media advertising and college-sponsored websites (Cormier et al., 2024). According to the qualitative implementation study, many colleges created G3-focused websites with contact forms, connecting prospective students to advisors for personalized application and financial aid guidance. However, qualitative evidence from eight of the 23 colleges revealed that many institutions did not limit G3-funded advisors to G3 students, instead assigning them to serve students across all programs. These implementation details suggest that while the marketing component was uniformly implemented, academic advising may have been diluted by offering targeted support to a broader student population.

The vast majority—90 percent— of G3 funding was earmarked for financial aid, addressing

[2] SB1100 legislative amendment retrieved from
https://budget.lis.virginia.gov/amendment/2021/1/SB1100/Introduced/MR/220/3s/

structural barriers through last-dollar scholarships and living stipends. In addition to covering remaining tuition costs after federal financial aid, G3 provided Student Incentive Success Grants (SSIG) of up to $900 per semester for full Pell-eligible students enrolled in at least 12 credits. These stipends targeted the lowest-income students, whose tuition was already covered by other sources, to help offset living expenses.

Although G3 involved some curricular changes, they were relatively minor. The original legislation specified eligible programs by CIP codes, with the VCCS implementing an approval process for colleges to submit individual programs for consideration. To qualify programs had to meet three criteria. First, they needed to be associated with eligible CIP codes codified in the original legislation. Second, they had to specify whether they allowed students to earn multiple levels of credentials, 'stackable credentials,' enabling participants to enter the workforce and return for further training as needed. Last, they were required to be eligible for federal financial aid, requiring at least 18 credit hours. In practice, all programs meeting these criteria were approved by the VCCS.[3]

G3 aimed to achieve several goals for low- and middle-income students by addressing three key behaviors. Importantly, it sought to increase enrollment in the high-demand occupational training programs identified by VOEE, (e.g., healthcare and technology). Second, the program attempted to improve access by addressing financial, informational, and logistical barriers that often hinder prospective students through simplified and tailored 'free college' messaging for targeted programs. Last, it sought to improve completion rates by offering dedicated counseling to help students select a program and assist in obtaining financial aid. By combining tuition-free access with a workforce-aligned structure, the program sought to meet student needs and employer demands.

2.2 Theoretical Framework

A key motivation for tuition-free community college initiatives is that financial constraints may limit students' ability to enroll in and complete postsecondary education. While credit constraints

[3]Personal communication with VCCS administrator October 6, 2023.

are a well-documented barrier (Carneiro & Heckman, 2002; Sun & Yannelis, 2016), tuition-free programs like G3 function primarily as last-dollar scholarships, meaning their direct financial benefits accrue most to students who do not already qualify for full tuition coverage through existing programs. This structure suggests that middle-income students–who face significant tuition gaps but are less likely to qualify for Pell Grants–are likely to benefit the most. However, recent evidence suggests that informational and logistical barriers, rather than direct financial costs, play a critical role in shaping college access and completion (Bettinger et al., 2012; Dynarski & Scott-Clayton, 2006). G3's investment in additional college advisors is intended to address these frictions, particularly by supporting FAFSA completion and helping students navigate program requirements.

At the same time, tuition-free programs may introduce substitution effects that alter postsecondary choices. Research on similar initiatives suggests that while eliminating tuition costs increases two-year college enrollment, increases in overall college enrollment may be partially offset by reductions in four-year college enrollment (Gurantz, 2020; Nguyen, 2020). G3's workforce-oriented structure raises additional concerns that restricting aid to specific fields may not only guide students toward high-demand sectors but also limit their broader educational and career flexibility. If financial incentives for degrees in high-demand fields redirect students toward high-demand industries, they may reduce information asymmetries and align postsecondary training with workforce needs. This may be welcome given previous studies that find students often misjudge labor market returns, leading to low participation in high-return fields (Baker et al., 2018).

Our study also contributes to research evaluating state and institutional efforts to align community college programming with local workforce needs. Workforce development has driven community colleges' mission since their inception, and policymakers increasingly leverage these institutions to address current and projected worker shortages (D'Amico, 2016). Strohl et al. (2024) estimate that half of the certificate and associate degrees awarded would need to shift to different fields to meet projected labor market demand over the next decade. By incentivizing enrollment in specific workforce-aligned programs, tuition-free initiatives like G3 may yield substantial economic returns and better align credentials with local employer needs (Bartik et al., 2021). Again, such policies may also introduce trade-offs, particularly regarding bachelor's degree attainment.

While workforce-oriented tuition programs may be designed to expand access–such as for high school graduates on the margin of college entry or adults considering a return to school–evidence suggests that inducing these students to enroll remains a challenge (Bonilla & Thim, 2025; Cellini, 2006; Gurantz, 2020; House & Dell, 2020). Instead, some portion of students who respond to these workforce-oriented initiatives could be diverted from higher-return associate or bachelor's degree pathways to shorter-term credentials.

Finally, this study contributes to the literature on the role of academic advising in community colleges. While the vast majority–90 percent– of G3 funds was allocated to financial aid, the remaining funds supported additional college advisors to assist students in navigating college admissions, financial aid, and program requirements (LIS, 2021). College advisors play an important role in supporting student goals and influencing student-decision making around program selection, enrollment intensity, and career choices (McKinney et al., 2024; Scott-Clayton, 2015). Experimental evidence from Bettinger & Baker (2014) and quasi-experimental evidence from Bahr (2008) highlight the potential for college coaches and advisors to improve student persistence and degree completion, particularly for nontraditional students in higher education and students attending community colleges. Increased exposure to college advising as a result of G3 may similarly work to improve student decision-making and observed academic and career outcomes.

2.3 Related Literature

This study contributes to two strands of empirical literature: the first examines the effects of statewide free college initiatives on college access and success, while the second evaluates state and institutional efforts to align college programming with local workforce needs. A majority of states have implemented free college initiatives as part of a grassroots effort to improve college affordability (Miller-Adams, 2021). Some initiatives impose means-testing or merit-based requirements while others require recipients to work in-state post-graduation, maintain academic progress, apply to only 2- or 4-year college students, or enroll in specific programs (Perna & Leigh, 2018). To date, most statewide free college initiatives operate as last-dollar scholarships, covering tuition and fees only after existing grant aid–such as Pell Grants–has been applied, and are typically limited to community college students who are state residents.

Empirical studies suggest that these programs demonstrate positive short-term impacts on community college enrollment, reduce loan borrowing, and improve financial aid access (Gurantz, 2020; House & Dell, 2020; Lowry & Li, 2022; Nguyen, 2020; Odle et al., 2021). Research on programs in Tennessee and Oregon also indicate the potential for diversionary effects, shifting some students into community colleges who would have otherwise enrolled at four-year colleges (Gurantz, 2020; House & Dell, 2020; Nguyen, 2020). Studies examining educational attainment, such as credential completion, are limited and show mixed results. Some initiatives show improvements (Bartik et al., 2021) while others report modest or unclear effects (Bell & Gándara, 2021; Li & Lowry, 2022; Ratledge et al., 2021). These findings suggest that while tuition-free initiatives expand access, their effects on long-term educational attainment remain uncertain–particularly in the context of eligibility restrictions for workforce-aligned programs.

The broader financial aid literature underscores that reducing uncertainty about college costs is a key mechanism for increasing postsecondary enrollment and persistence (Dynarski et al., 2021; Dynarski, Page, & Scott-Clayton, 2023). Free college programs with transparent messaging and simple eligibility criteria tend to have higher take-up rates, whereas programs with complex requirements–such as New York State's Excelsior Scholarship– have experienced limited participation due to administrative hurdles like the in-state work requirement (Scott-Clayton et al., 2022). However, limited research has examined how program-specific eligibility, such as those in workforce-oriented free college programs affect student outcomes. Prior studies highlight the potential for differential tuition pricing to increase or decrease credentials awarded in specific program areas, but these studies focus exclusively on four-year universities and program areas differ from those deemed eligible for G3 aid (Acton, 2021; Kelchen, 2025; Stange, 2015). This study extends the literature by examining the effects of Virginia's G3 initiative–one of a growing number of programs explicitly tied to workforce needs–on community college student enrollment, financial aid access, and early academic outcomes.

3 Methods

3.1 Pre-Registration

Understanding causal impacts is crucial for informing policy decisions, particularly as advancements in quasi-experimental methods have heightened awareness of issues such as specification searching or "p-hacking" (Brodeur et al., 2020). To reduce the risks associated with researcher discretion in design choices and outcome selection, we preregistered our analysis plan. This preregistration specified the intervention, confirmatory outcomes (FAFSA completion, grant aid received, and academic attainment), exploratory outcomes, heterogeneity analyses, and multiple-comparison adjustments (Bonilla & Sparks, 2024; Nosek et al., 2018).

Because pre-registering quasi-experimental analyses is uncommon, our plan noted that we would document deviations to address empirical challenges. Consistent with that commitment, we submitted a detailed transparent-changes document explaining our use of an identification strategy that was not specified in the initial plan. Specifically, we found that self-selection into G3 programs posed a challenge for the preregistered DID approach, which relies on empirical evidence in support of the parallel trends assumption. This assumption may be violated if program participation and outcomes evolve differently across groups. To address this, we estimate a difference-in-discontinuity (RD-DD) design, which exploits the sharp income eligibility threshold to provide local estimates of causal effects. Unlike a canonical DID, the RD-DD compares local discontinuities at the FPL threshold across groups and cohorts, thereby controlling for threshold-specific shocks without relying on parallel trends holding across all income levels. Importantly, the RD-DD design improves internal validity, but it does not alter the intervention studied nor the outcomes analyzed.

3.2 Difference-in-Discontinuity

A baseline specification for an RD design would estimate the local average treatment effect of G3 eligibility on financial aid and academic outcomes for students near the 400 percent federal poverty level (FPL) eligibility threshold. This approach leverages the sharp income-based eligibility rule, comparing outcomes for students just above and below the threshold in the 2021 and 2022 entry cohorts. While the RD design offers strong internal validity by exploiting local randomization at the FPL threshold, it faces two limitations in this context. First, the relatively small sample near the threshold limits precision. Second, any other policy or economic changes occurring at the same FPL cutoff, or changes in the composition of students at the threshold across cohorts, could bias estimates.

To address these concerns, our preferred design is a difference-in-discontinuity (RR-DD), which combines the strengths of RD with variation in both G3 program enrollment and enrollment across cohorts (Grembi et al., 2016). The RD-DD retains the internal validity of the threshold comparison while differencing out any discontinuities that appear among contemporaneous non-G3 program enrollees and by incorporating pre-policy cohorts of both G3 and non-G3 students. In doing so, it directly addresses the major threat to a cross-sectional RD—co-occurring shocks at the same threshold—while also accounting for potential cohort-specific selection at the FPL cutoff and improving statistical precision.

In this framework, we build on the cross-sectional RD estimator, which originally focuses on post-policy adoption G3 students, by incorporating three additional groups: (1) contemporaneous cohorts that did not enroll in G3 programs, (2) pre-intervention G3 students, and (3) pre-intervention non-G3 students (See Appendix A). This specification modifies the RD model in equation 3 by differencing out the corresponding threshold effects from the non-G3 comparison groups. Specifically, it modifies the baseline RD model by interacting each term with indicators for enrollment in a G3 program and for being in the post period:

$$Y_{ist} = \delta[I(FPL_i \leq 400) \times G3_i \times Post_t] + f(FPL_i) + I(G3_i) + \eta_{st} + \boldsymbol{X}_i + \epsilon_{ist} \quad (1)$$

δ captures the differential effect of income-eligibility among G3 students in the post-period versus ineligible students. The function $f(FPL_i)$ is specified flexibly and interacted with $G3_i$ and $Post_t$ indicators, ensuring that all lower-order interactions are included in the model. To assess sensitivity to functional form, we estimate specifications with both linear and quadratic polynomials, vary the bandwidth around the threshold, and implement alternative weighting approaches (e.g., kernel, uniform). Our preferred models include a vector of student-level baseline covariates ($\boldsymbol{X}$) and institution by entry cohort fixed effects ($\eta_s t$). Throughout the paper we cluster standard errors at the institution by cohort level[4].

By comparing threshold effects across treated (G3 post-intervention) and untreated (non-G3 and pre-intervention) students, the RD-DD framework strengthens causal identification by verifying that non-G3 post-intervention students received no additional financial aid at the threshold. The design requires that baseline characteristics at the 400 percent FPL threshold remain smooth across the assignment threshold, which we verify in balance tests. The RD-DD approach incorporates a contemporaneous non-G3 comparison group that faces similar labor market conditions and enrolls at the same institutions, allowing us to account for identical campus-level policies. It also incorporates pre-intervention G3 students who choose similar programs of study prior to G3 aid availability, guarding against concerns that selection into G3 fields biases estimated effects. Together, these comparisons ensure that the RD-DD isolates the causal effect of G3 at the income eligibility threshold rather than capturing co-occurring shocks or compositional changes.

For the RD-DD design to yield unbiased estimates, the same core assumptions required for a valid RD must hold. First, students just above and below the threshold must be comparable. In other words, in the absence of G3, the relationship between income and outcomes would be smooth across the 400 FPL threshold. We assess this by testing the smoothness of baseline covariates (See Table 2). Second, students must not be able to manipulate their treatment status by systematically sorting just above or below the threshold to qualify for aid. We employ density tests to detect potential heaping or discontinuities in income (Figure 1a) and find no evidence of manipulation. We also consider institutional details in addition to the empirical evidence. The structure of the FAFSA application process, which determines financial aid based on prior-prior year income, further supports the validity of the RD-DD design. Since income eligibility was determined from tax records from two years before enrollment, students had limited ability to strategically adjust their reported income. Additionally, while the G3 income threshold was publicly advertised as "around $100,000 for a family of four," the exact dollar amount varied by household size and was

[4]We also cluster standard errors at the two-digit program CIP code by institution level and find qualitatively similar results

not explicitly disclosed in recruitment materials. These factors reduce the likelihood of strategic income adjustments to qualify.

Because the RD-DD builds on the RD by differencing out discontinuities observed in non-G3 programs, these assumptions ensure that any discontinuous change at the threshold in the post-period can be attributed to G3 rather than to sorting or underlying trends.

3.3 Complementary DID Specifications

While the RD-DD design provides the most internally valid estimates of G3's impact near the income eligibility threshold, its scope is necessarily local–focused on FAFSA completers who selected into G3-eligible programs. To analyze and assess one of our confirmatory outcomes, FAFSA completion, as well as the potential generalizability of findings, we complement the RD-DD with event study and DID models. The DID framework compares changes in outcomes for income-eligible students enrolled in G3-eligible programs (treatment group) to those in ineligible programs (comparison group) before and after the policy's adoption. Because the policy is implemented at a single point in time, this approach does not rely on variation in treatment timing but instead assumes that, absent G3, outcomes for treatment and comparison students would have followed parallel trends. Our main DID model is specified in Equation 2:

$$Y_{it} = \delta(G3_{it}) + D_i + \omega_t + \boldsymbol{X}_i + \alpha_s + \epsilon_{it} \tag{2}$$

where Y_{it} represents financial aid and academic outcomes of interest for student i in entry cohort t, D_i is a binary indicator for enrollment in a G3 program, and ω_t represents fixed effects for entry cohort year. The parameter of interest, δ, represents the ITT effect of post-policy enrollment in a G3 program. Institution-level fixed effects, α_s control for time invariant institutional factors such as resources, capacity, faculty quality and labor market conditions that differ across institutions and ensure that any observed effects are not driven by differences across institutions. While we cluster standard errors at the institution-by-cohort level, we also cluster at the program-by-cohort level and find qualitatively similar results.

To assess the key parallel trends assumption, we implement event study analyses, which also allow us to examine anticipatory responses. We consider additional assumptions relevant to DID identification in turn. First, no anticipatory effects requires that institutional responses to the G3 policy did not alter student behavior before its formal implementation. However, institutional responses—including adjustments to curricular and programmatic offerings, and administrative processes—may have taken place following the policy announcement. We document evidence that institutions increased the number of G3-eligible programs and that student enrollment in these programs grew in the lead-up to the policy's roll out (Sparks & Bonilla, 2024). Second, stability in the composition of treatment and comparison groups over time is necessary to ensure that observed effects do not reflect selection dynamics. Our empirical checks confirm that no G3 financial aid was administered prior to the program's adoption, partially satisfying this assumption (Figure A1). We also assess group stability through balance tests on student demographics and enrollment patterns, which suggest that DID observed effects may, in part, reflect selection dynamics rather than causal impacts.

Finally, consistent with our preregistration, we estimate two additional panel-based DID models (see Appendix A). While these analyses enrich our understanding of how G3 shaped financial aid and enrollment more broadly, we interpret them as complementary evidence that contextualizes the policy's general impact rather than as substitutes for the internally valid RD-DD estimates.

4 Data and Analytic Sample

Our data come from the Virginia Community College System (VCCS) for academic years 2016-17 through 2023-24. The data include information on student demographics, course and program enrollment, financial aid receipt, and degree completion records. Eligibility for G3 program designation was determined by state workforce and income criteria established by the Virginia legislature and other governmental agencies. Initially, the legislature defined G3 eligibility based on regional workforce needs assessments conducted by the Virginia Office of Education Economics (VOEE, 2023). We identify G3-eligible programs by their corresponding 6-digit CIP codes from the VCCS-approved list, and whether each program received G3 program approval through the State

Board for Community Colleges (SBCC) application process. Additionally, students are flagged as income-eligible for G3 if they (1) completed the FAFSA and (2) reported a family income of less than 400 percent of the Federal Poverty Level (FPL), adjusted for family size.

The analysis focuses on financial aid and academic outcomes, with five designated as pre-registered confirmatory outcomes. FAFSA completion and total grant aid are the primary financial aid outcomes of interest (confirmatory), while G3 and SSIG aid, as well as total loans, are considered exploratory outcomes. We include additional results that examine federal, state, and institutional grant aid to complement our confirmatory findings. Academic outcomes include any degree and certificate completion within 2 years of entry (confirmatory). Any degree includes credentials besides certificates such as associate and applied associate degrees.

To construct our analytic sample, we make several important exclusions. First, we excluded students who enrolled exclusively in a Virginia community college through dual enrollment or other programs that allow high school students to complete college-level coursework at community colleges, as these students are ineligible for the focal treatment, covering approximately 18 percent of overall FTIC enrollments. Second, we exclude non-resident students, who are either ineligible to file a FAFSA (due to non-permanent resident or non-citizen status) or do not qualify for G3 financial aid (n=10,241 , or 4 percent of FTIC sample). Finally, we exclude students missing critical administrative records, such as FAFSA completion, transcripts, program of study, or entry cohort data (n=26,111 , or 12 percent of FTIC sample).

The full analytic sample comprises nearly 175,000 first-time-in-college (FTIC) students from seven entry cohorts, all of whom enrolled in either short-term credential or associate degree programs at one of Virginia's 23 community colleges. We present summary statistics for the full sample in Column 1 of Table 1. The sample is both racially and socioeconomically diverse: over 40 percent identify as a person of color, 57 percent received grant aid, and 55 percent of FAFSA filers reported a family income below 200 percent of the federal poverty level (i.e., 0.367/0.662).

Columns 2 and 3 provide summary statistics for students who completed a FAFSA and students in our difference in discontinuity (RD-DD) sample, respectively. The RD-DD sample includes those who completed a FAFSA, reported family income below 1,000 percent of FPL, and were prime working age upon entry (i.e., 18-54). A similar proportion of students in the RD-DD sample enrolled in (and completed) certificate programs. However, this masks differences between G3 program enrollees who were more likely to enroll in certificate programs (47 versus 10 percent). Demographically, the RD-DD sample has a higher proportion of Black students (22 versus 19 percent) fewer White students (46 versus 51 percent), and more students from lower income backgrounds (56 versus 37 percent) relative to the broader VCCS population. Nearly 1 in 2 students who enrolled in G3 programs post-policy adoption received G3 or SSIG aid, and relatively few of them took out loans (8.5 percent). Across the samples educational attainment is indicative of low completion rates at community colleges: only 15 percent of students earned any degree within 2 years, with just over half of these students earning certificates as opposed to associate degrees.

5 Results

5.1 Evidence from Difference-in-Discontinuity Design

We first present results from our RD-DD design, which estimates the effect of G3 eligibility on financial aid and academic outcomes for students at the income eligibility threshold. The top row of Table 2 reports first-stage reduced-form estimates on G3 aid receipt for the full RD-DD sample and within bandwidths of the income eligibility threshold. These results confirm a large and discontinuous 93 percentage-point increase in G3 aid receipt at the 400 percent FPL threshold. These results remain robust to demographic controls and various bandwidth restrictions. Figure 1a confirms no evidence of manipulation at threshold, while Figure 1b illustrates high compliance, with no students above the 400 percent FPL threshold receiving G3 aid. In Appendix Figure A1 we provide a full set of visuals by subgroup (G3 vs. non-G3, pre- vs. post-adoption), showing that only G3 enrollees in the post-adoption period exhibit a discontinuity in aid receipt at the 400 percent FPL threshold. Auxiliary RD models in Table 2 indicate no statistically significant differences in baseline demographics–including gender, age, race, dependency status, family size and income–at the eligibility threshold. Together, these findings confirm that the RD-DD design meets key assumptions for internal validity, with no evidence of sorting and high compliance with G3 eligibility criteria.

Table 3 presents reduced-form RD-DD estimates for confirmatory financial aid outcomes for the full sample and within one standard deviation of the assignment variable. G3 increased total grant aid by $1,700 to $2,400 and total financial aid by roughly by $1,100 to $1,800, with the $600 discrepancy reflecting a reduction in student borrowing. These figures translate to a 20 to 30 percent increase in total grant aid (mean aid $5,000). Visuals confirm that discontinuous shifts in aid receipt are only present for the ITT sample (Appendix Figure A2).

Table 4 shows results for academic outcomes, revealing a pronounced 5.1 to 6.7 percentage point increase in certificate completion and 5.1 to 5.6 percentage point increase in any degree received. The estimates for degree and certificate completion are positive and of a similar magnitude as the full sample estimates, however, standard errors increase by 50 to 75 percent in estimates for tighter bandwidths and conventional levels of statistical significance are not met. Strikingly, the magnitude of the estimates are consistent, suggesting that G3 increased certificate completion rates while having no detectable effect on associate degree completion.

Financial aid and credential completion findings are robust to alternative model specifications and bandwidth restrictions (Table 5). Linear estimates of the effect of G3 from increasingly tighter bandwidths around the assignment threshold confirm that grant aid increased by just over $2,200 and borrowing decreased by around $500 resulting in a total financial aid increase of $1,700. G3 aid reduced student borrowing and displaced some state and institutional grant aid, with no detectable effect on federal grants; nevertheless, overall grant aid and total financial aid increased (Appendix Table A1).

A potential concern is whether other policies or structural factors at the 400 percent FPL threshold confound the estimated effects. Our visuals at the 400 percent FPL threshold reveal no discontinuities in financial aid (Appendix Figure A2), strengthening our causal interpretation that the observed effects are driven by G3 eligibility rather than other income-related policies or institutional practices. The visuals for degree completion reveal a pattern suggesting that G3 program enrollees increased their certificate completion rates post-policy adoption while non-G3 program enrollees experienced declines in certificate completion relative to the pre-adoption period (Appendix Figure A3. Unconditional means of G3 and non-G3 pre- and post-policy implementation groups further underscore that G3 aid may helped income-eligible students increase or at least maintain the likelihood of certificate completion while all other groups experienced declines (Appendix Figure A4).

Taken together, these results provide the most credible causal estimates of G3's effect on our pre-registered outcomes. The magnitude and consistency of the financial aid findings across bandwidths and specifications provide strong evidence of G3's impact at the income eligibility threshold. The RD-DD framework incorporates untreated students enrolled in non-G3 programs and students in the pre-policy period to isolate the causal effect of financial aid eligibility under G3. These findings show that completion rates in G3 programs rose over time relative to non-G3 programs. We next examine the broader effects of G3 on our confirmatory outcomes using event study models.

5.2 Evidence from Event Study and DID Analyses

The RD-DD results provide unbiased and internally valid local treatment effects, but they may not generalize to students with lower incomes–those further from the eligibility threshold. We therefore use panel-based estimators primarily as robustness checks to explore the generalizability of findings and capture broader policy effects following G3 implementation in 2021.

FAFSA Completion & Compositional Changes

The internal validity of the DID estimation strategy relies on the untestable assumption that, in the absence of G3 policy adoption, outcomes for treated and control groups would have evolved in parallel. In addition to testing pretrends, we examine whether the treated cohort experienced compositional changes inconsistent with those of the control group. Findings from a DID specification (Table 6) and event study models (Tables A2 & A3) suggest that the G3 policy resulted in increased FAFSA completion among students enrolled in G3-eligible programs and shifted the sociodemographic profile of enrollees–specifically, increasing the share of students identifying as Black and decreasing the share identifying as White. The proportion of students from middle-income households also increased, which is unsurprising given these students stood to gain the most financially from the policy's last-dollar scholarship design. These changes are salient for policymakers, as FAFSA completion was required to access G3 aid and to increase take-up of existing federal aid for eligible students. However, these compositional changes raise concerns about the internal validity of the DID approach, as they may violate the parallel trends assumption and introduce bias, the direction of which remains uncertain.

Financial Aid & Educational Attainment

Figure 2 presents event study estimates for financial aid and educational attainment, showing no significant pre-trends and sharp increases in financial aid and certificate completion following G3 implementation. Total grant and total financial aid increased by $768 and $626, respectively, with grant aid driven by G3 funds rather than other federal, state, or institutional grant aid (see Figure A5 and Table A4).[5] Degree completion rose by 3.5 percentage points for the first cohort and 5 percentage points for the second cohort, largely due to gains in certificate completion.[6]

We next report findings from our main DID and synthetic DID specifications. Table 7 presents our main estimates for financial aid outcomes, showing that students in G3-eligible programs received the targeted aid as intended. The DID specification in the top panel of Table 7 shows increases in total grant aid of nearly $600 from a baseline amount of $4,795 — a 13 percent increase in total grant aid. Results from the synthetic DID model, which aggregates data by campus and cohort, corroborate these findings (see Table 7). The SDID approach helps mitigate pre-treatment trend violations, though it cannot fully account for compositional changes. Our exploratory estimates of borrowing, inferred from the difference between total grant and financial aid, suggest small but consistent reductions. At baseline, only 10 percent of students relied on loans, and average borrowing was $483. While the decline in borrowing was modest, the magnitude of the implied effect is large and consistent with reductions in borrowing observed in the RD-DD frame-

[5]Joint F-tests for pre-trends and corresponding p-values presented in the appendix confirm that there are no significant differences in year-over-year changes in total grant aid, total financial aid, any degree completion, and certificate completion prior to policy implementation for students enrolled in G3-eligible versus ineligible programs (Table A3)

[6]Increases in financial aid are statistically significant at the ($p < .001$) level, whereas increases in degree completion are significant at conventional levels of ($p < .01$) and ($p < .05$). Our pre-registration plan specified ($p < .01$) for our confirmatory outcomes to adjust for examining multiple outcomes.

work.

Table 7 also presents our main estimates for educational attainment. The DID specification shows that degree completion increased by 4.9 to 5.1 percentage points, from a baseline rate of 15 percent, primarily driven by certificate completion. This intent-to-treat sample includes students eligible for both aid and non-aid components of the G3 intervention. The SDID estimates corroborate the DID estimates, indicating that certificate completion increased, while associate degree completion was largely unaffected. Even though these models control for initial program level of enrollment (e.g. certificate versus associate degree), we may still be concerned that observed increases in certificate completion partially reflect differences in G3-eligible versus ineligible program length. Descriptively, G3 and non-G3 certificate programs have comparable credit hour requirements. Still, to account for this further, we show results from panel-based estimators on a sample restricted to students who entered into certificate programs in the appendix (see Table A5). These results similarly suggest that aid-eligible students in G3 programs were about 6 percentage points more likely to complete a certificate compared to students in other programs. In sum, panel-based estimates more generally corroborate the RD-DD findings: G3 increased financial aid and certificate attainment but had minimal impact on associate degree completion. These effects appear to be driven by both increases in aid and exposure to G3 curricula and programmatic supports.

Treatment Heterogeneity

We explore treatment heterogeneity across G3 sectors and student sociodemographic groups, including income level, gender, and age. We find that there are sector-specific differences in educational attainment driven by the male-dominated manufacturing programs of study (Figure A6). Relative to other G3-eligible programs, manufacturing programs had shorter average program duration and time to degree completion, perhaps contributing to larger observed effects within two years of entry. Analysis by gender specific subgroups shows that the educational attainment increases are driven by males and those younger than 25 years old. As a last dollar scholarship, the increase in total grant aid accrued to middle income students with household incomes from 200 to 400 percent of FPL, an additional $1,100 in total grant aid. However, degree completion rates increased at comparable rates for these students compared to students with lower reported family income who received less additional aid from G3 on average ($482). We find no differences for students from different racial/ethnic groups, and effects on degree completion within two years were broadly positive and driven by increases in certificate completion (see Figure A7).

6 Discussion

We provide quasi-experimental evidence that Virginia's G3 program expanded financial aid access, increased grant aid and reduced student borrowing while increasing short-term credential completion in targeted high-demand fields. Difference in discontinuity estimates, which provide the most credibly causal evidence, indicate that G3 eligibility led to a substantial increase in grant aid–approximately $1,800 per year on average–and a reduction in borrowing of about $600. These gains occurred at the 400% FPL income eligibility threshold, which is roughly equivalent to an annual income of $60,000-120,000 depending on family size. Given that students in this income range are typically ineligible for full Pell support, G3 addressed a notable affordability gap among middle-income students. These findings are consistent with economic theory predicting that last-dollar aid programs will have the greatest financial impact on students who are not fully subsidized by federal aid, reducing credit constraints and improving college affordability.

Consistent with G3's design, difference-in-discontinuity estimates show no evidence of aid receipt among ineligible students and no discontinuities in financial aid among non-G3 students, reinforcing the credibility of the findings. While financial aid impacts are clear, academic effects at the threshold indicate a 6 percentage point increase in certificate completion, but these gains in part stem from declining completion rates for comparison students. The legislation was introduced as a pandemic recovery strategy, and in this respect, G3 aid stabilized completion rates for eligible students rather than generating new gains. This pattern reinforces the view that while financial aid may improve access it is not always sufficient to move academic outcomes on its own, particularly in community college settings where other structural and information barriers are salient (Dynarski & Scott-Clayton, 2006; Bettinger et al., 2012; Dynarski et al., 2023).

Taken together with the observed enrollment increases in designated G3 programs (Sparks &

Bonilla, 2025), these findings indicate that the number of students completing certificates rose–providing evidence that G3 expanded the supply of certified workers in targeted fields, rather than suppressing completion rates. Robustness checks using difference-in-difference models add additional insights into whether these effects generalize to a broader set of students, including those further from the income threshold. Overall the DID findings suggest that financial aid impacts were most pronounced for upper middle income students, while certificate completion effects were broadly similar across the income distribution. Although these estimates are consistent with those from the difference-in-discontinuity design, the potential for selection dynamics limits their causal interpretation. We therefore view the DID evidence as suggestively consistent with the locally estimated findings that G3 had financial aid and certificate completion impacts.

Large estimated effects on certificate completion from RD-DD and panel-based estimators may reflect the value of non-financial aid program components such as targeted messaging and labeling of G3 programs as 'high-demand.' For instance, we found suggestive evidence of gains in certificate completion among aid-ineligible students who enrolled in G3 programs and may have benefited from these non-aid components (see Table A6). These findings are in line with the existing literature suggesting that simplified information and program structure–such as signaling high-return career paths–can shape student behavior even in the absence of financial incentives (Baker et al., 2018). Second, evidence from our panel-based estimators suggests that students responded to the G3 policy by shifting enrollment into eligible programs. These compositional shifts could inflate estimated effects on certificate completion from panel-based methods if student groups with higher average baseline completion rates were more likely to enroll in G3-eligible programs after policy implementation. This does not appear to be the case necessarily, as some some student groups with lower than average baseline completion rates were most likely to shift into G3 programs. Importantly, at baseline students in G3 programs were about twice as likely to complete a certificate within two years of entry compared to students in non-G3 programs. Observed effects from panel-based estimators may, in part, reflect this shift of students into programs that have historically had more success in ensuring students complete short-term certificate programs.

Across all models, effects on any degree completion beyond certificates remained negligible.

These patterns reflect G3's design and intent: to expand workforce credentialing rather than promote associate degree completion or vertical transfer to four-year institutions. Incentivizing and supporting students to complete shorter-term credentials may offer a low-barrier entry point to the labor market for students not otherwise on track to complete an associate degree. However, the economic returns to certificates are typically lower than associate degrees, both in the short and longer term (Minaya & Scott-Clayton, 2022).

Several factors may help explain the limited effects on degree completion beyond certificates and relative to the size of the aid increases. First, many students may have been unaware of G3 aid receipt, limiting the salience of financial incentives (Cormier et al., 2024). Second, research has shown that financial aid alone, especially when complex or opaque, may not be sufficient to substantially shift postsecondary attainment (Dynarski et al., 2023). This is particularly relevant in community college contexts, where significant structural barriers exist beyond tuition costs. Moreover, while increased exposure to counselors was a core goal of G3, we are not able to adequately isolate the effects of this program component. Implementation research from Cormier and coauthors (2024) suggests that counselors hired through G3 funds were frequently asked to support students who may not have been eligible for G3 aid. Treatment spillover may help to explain detected effects on the placebo group of students who were enrolled in G3 programs but not eligible for G3 aid. Future research should work to disentangle and better isolate the effects of counselors on community college student outcomes by collecting more nuanced data on student exposure to counselors.

The G3 program's design–restricted to high-demand workforce programs–narrowed its scope but likely enhanced its political and fiscal sustainability. By explicitly tying tuition-free access to labor market needs, the policy garnered bipartisan support, and had staying power after a shift in party control of the state legislator and governor's office (Collum, 2022). Notably, several states, such as Arkansas, Indiana, Kentucky, and New York, have recently adopted similar workforce-targeted free college policies. These initiatives have the potential to support greater alignment between community college programming and local labor market needs. Early evidence from G3 suggests that such programs can meaningfully expand access to aid and improve short-term credentialing outcomes, particularly for middle-income and underserved students.

These findings carry several implications for policymakers. First, simple and well-targeted financial aid programs appear most effective when paired with implementation support– such as proactive advertising and application assistance. In the case of G3, Virginia provided marketing toolkits and 10 percent of funds to advising, helping students complete FAFSA and navigate requirements. Given the recent challenges with FAFSA administration, these wraparound supports may have been critical and, indeed, appear to have contributed to significant increases in FAFSA completion. Second, workforce-aligned free college initiatives may boost enrollment in and completion of short-term credentials, potentially increasing the share of credentialed workers in high-demand fields. These were central goals of the policy that reflect grant aid incentives as a mechanism for improving college access and success while addressing local labor market needs. We cannot extrapolate credential completion results to a longer time horizon or draw more definitive conclusions on the policy effects on longer-term human capital accumulation. Accordingly, future research should examine further whether G3 and similar policies are carefully designed to ensure they do not unintentionally divert students from higher-return degree pathways and that pathways for subsequent educational attainment are clearly articulated.

Overall, Virginia's G3 program significantly increased enrollment in workforce targeted programs and improved access to financial aid while reducing borrowing among income-eligible students, with evidence of gains in certificate completion. These results align with G3's emphasis on quick transitions from community college into the labor market. Our study's time frame limits the ability to fully assess whether G3 promotes optimal (or suboptimal) human capital accumulation, especially as associate degrees take over 5 years to complete on average (Shapiro et al., 2016). Furthermore, due to the lack of data on student transfer outcomes, we cannot estimate the effect of G3 on subsequent enrollment at four-year institutions. While effects on associate degrees were negligible, the program may have helped bring new students into postsecondary education. Future research should examine the labor market returns to G3 credentials, track longer-term academic attainment, and assess whether the program improved alignment between community college training and workforce participation.

7 References

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives, 33(2)*, 3-30.

Acton, R. (2021). Effects of reduced community college tuition on college choices and degree completion. textitEducation Finance and Policy, 16(3), 388-417.

Autor, D.H. (2014). Skills, Education, and the Rise of Earnings Inequality among the 'Other 99 Percent'. *Science, 344(6186)*, 843-51.

Bahr, P. R. (2008). Cooling out in the community college: What is the effect of academic advising on students' chances of success?. *Research in Higher Education, 49*, 704-732.

Baker, R., Bettinger, E., Jacob, B., & Marinescu, I. (2018). The effect of labor market information on community college students' major choice. *Economics of Education Review, 65*, 18-30.

Bartik, T. J., Hershbein, B., & Lachowska, M. (2021). The effects of the Kalamazoo Promise Scholarship on college enrollment and completion. *Journal of Human Resources, 56(1)*, 269-310.

Bartik, T. J., Miller-Adams, M., Pittelko, B., & Timmeney, B. F. (2021). Economic Costs and Benefits of Tuition-Free College in Illinois. Employment Research Newsletter, 28(4), 2.

Bell, E., & Gándara, D. (2021). Can free community college close racial disparities in postsecondary attainment? How Tulsa Achieves affects racially minoritized student outcomes. *American Educational Research Journal, 58(6)*, 1142-1177.

Bettinger, E. P., & Baker, R. B. (2014). The effects of student coaching: An evaluation of a randomized experiment in student advising. *Educational Evaluation and Policy Analysis, 36(1)*, 3-19.

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.

Bhargava, S., & Manoli, D. (2015). Psychological frictions and the incomplete take-up of social benefits: Evidence from an IRS field experiment. *American Economic Review, 105(11)*, 3489-3529.

Bonilla, S., & Sparks, D. (2024). Get a Skill, Get a Job, Get Ahead? Evaluating the Effects of Virginia's G3 Program. https://doi.org/10.17605/OSF.IO/7HT4A

Bonilla, S. & Thim, A. (forthcoming). The Effects of At-Scale Career Pathway Investments on the Transition from High School to College. *Education Finance & Policy*, 1-44. doi.org/10.1162/edfp_a_00445

Brodeur, A., Cook, N., & Heyes, A. (2020). Methods matter: P-hacking and publication bias in causal analysis in economics. *American Economic Review, 110(11)*, 3634-3660.

Budget Amendments SB1100 (2021). Virginia Legislative Information System. https://budget.lis.virginia.gov/amendment/2021/1/SB1100/Introduced/MR/220/3s/

Carneiro, P., & Heckman, J.J. (2002). The evidence on credit constraints in post-secondary schooling. *The Economic Journal*, 112(482), 705-734.

Cellini, S. R. (2006). Smoothing the transition to college? The effect of Tech-Prep programs on educational attainment. *Economics of education review, 25(4)*, 394-411.

Collum, G. (2022). How do promise programs benefit states? In Miller-Adams, M. & Iriti, J. (Eds). The Free College Handbook: A Practitioner's Guide to Promise Research. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research. https://research.upjohn.org/reports/283

Cormier, M., Kazis, R., Edgecombe, N., & Atkinson, M. (2024). Increasing Access to High-Demand Occupational Training: An Exploration of G3's Recruitment and Enrollment Strategies. ARCC Network Brief. *Community College Research Center, Teachers College, Columbia University*.

D'Amico, M. M. (2016). Community college workforce development in the student success era. *Higher education: Handbook of theory and research, 217-273*.

Deming, D.J. (2017). The Growing Importance of Social Skills in the Labor Market. *The Quarterly Journal of Economics, 132(4)*: 1593-1640.

Dynarski, S., Libassi, C. J., Michelmore, K., & Owen, S. (2021). Closing the gap: The effect of reducing complexity and uncertainty in college pricing on the choices of low-income students. *American Economic Review, 111(6)*, 1721-1756.

Dynarski, S., Page, L., & Scott-Clayton, J. (2023). College costs, financial aid, and student decisions. In *Handbook of the Economics of Education (Vol. 7, pp. 227-285)*. Elsevier.

Dynarski, S., Nurshatayeva, A., Page, L. C., & Scott-Clayton, J. (2023). Addressing nonfinancial barriers to college access and success: Evidence and policy implications. In *Handbook of the Economics of Education (Vol. 6, pp. 319-403)*. Elsevier.

Dynarski, S. M., & Scott-Clayton, J. E. (2006). The cost of complexity in federal student aid: Lessons from optimal tax theory and behavioral economics. *National Tax Journal*, 59(2), 319-356.

Grembi, V., Nannicini, T., & Troiano, U. (2016). Do fiscal rules matter?. *American Economic Journal: Applied Economics*, 8(3) 1-30.

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.

House, E., & Dell, M. (2020). Keeping the promise: Early outcomes of Tennessee's tuition-free college initiative. Improving research-based knowledge of college promise programs, 151-172.

Kelchen, R. (2025). Examining the effects of differential tuition policies on bachelor's degree completions. *AERA Open, 11*, 23328584251338155.

Li, A. & Lowry, D. (2022). Why do promise programs benefit students? In Miller-Adams, M. & Iriti, J. (Eds). The Free College Handbook: A Practitioner's Guide to Promise Research. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research. https://research.upjohn.org/reports/283

Lowry, D. & Li, A. (2022). How do promise programs benefit students? In Miller-Adams, M. & Iriti, J. (Eds). The Free College Handbook: A Practitioner's Guide to Promise Research. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research. https://research.upjohn.org/reports/283

McKinney, L., Bourdeau, G. V., Burridge, A. B., Lee, M., Miller-Waters, M., & Barnes, Y. M. (2024). " I Advise, You Decide": How Academic Advisors Shape Community College Students' Enrollment and Credit Load Decisions. *The Review of Higher Education*.

Miller-Adams, M. (2021). The path to free college: In pursuit of access, equity, and prosperity. Cambridge MA: Harvard Education Press.

Minaya, V., & Scott-Clayton, J. (2022). Labor market trajectories for community college graduates: How returns to certificates and associate's degrees evolve over time. *Education Finance and Policy, 17(1)*, 53-80.

Nguyen, H. (2020). Free college? Assessing enrollment responses to the Tennessee Promise program. *Labour Economics, 66*, 101882.

Nosek, B. A., Ebersole, C. R., DeHaven, A. C., & Mellor, D. T. (2018). The preregistration revolution. *Proceedings of the National Academy of Sciences, 115(11)*, 2600-2606.

Odle, T. K., Lee, J. C., & Gentile, S. P. (2021). Do promise programs reduce student loans? Evidence from Tennessee Promise. *The Journal of Higher Education, 92(6)*, 847-876.

Perna, L. W., & Leigh, E. W. (2018). Understanding the promise: A typology of state and local college promise programs. *Educational Researcher, 47(3)*, 155-180.

Ratledge, A., Sommo, C., Cullinan, D., O'Donoghue, R., Lepe, M., & Camo-Biogradlija, J. (2021). Motor City Momentum: Three Years of the Detroit Promise Path Program for Community College Students. MDRC.

Scott-Clayton, J. (2015). The shapeless river: Does a lack of structure inhibit students' progress at community colleges?. In Decision making for student success (pp. 102-123). Routledge.

Scott-Clayton, J., Libassi, C. J., & Sparks, D. (2022). The Fine Print on Free College: Who Benefits from New York's Excelsior Scholarship? An Essay for the Learning Curve. Urban Institute.

Shapiro, D., Dundar, A., Wakhungu, P.K., Yuan, X., Nathan, A, & Hwang, Y. (2016, September). Time to Degree: A National View of the Time Enrolled and Elapsed for Associate and Bachelor's Degree Earners (Signature Report No. 11). Herndon, VA: National Student Clearinghouse Research Center.

Sparks, D., & Bonilla, S. (2025). The Role of Policy Design in Free College Programs: Evidence from Virginia. *Education Finance and Policy*, 1-23.

Stanford, J. (2017). The resurgence of gig work: Historical and theoretical perspectives. *The Economic and Labour Relations Review, 28(3)*, 382-401.

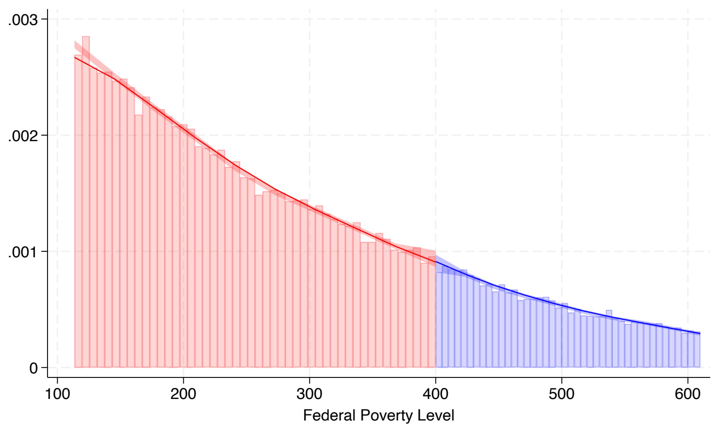
Stange, K. (2015). Differential pricing in undergraduate education: Effects on degree production by field. *Journal of Policy Analysis and Management*, *34(1)*, 107-135.

Strohl, J., Mabel, Z., & Campbell, K. P. (2024). The Great Misalignment: Addressing the Mismatch between the Supply of Certificates and Associate's Degrees and the Future Demand for Workers in 565 US Labor Markets. Georgetown University Center on Education and the Workforce.

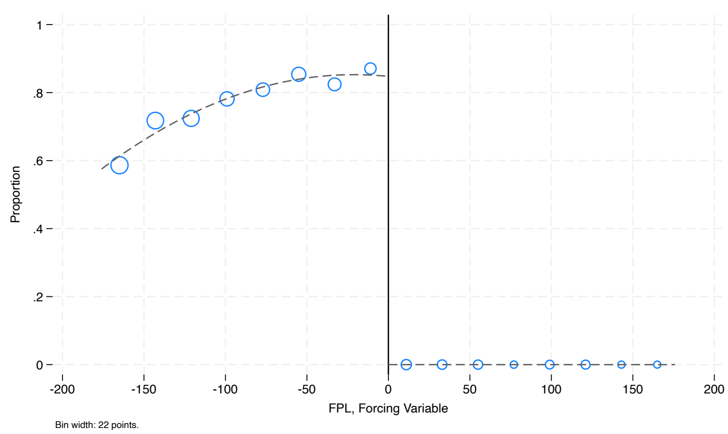
Sun, S. T., & Yannelis, C. (2016). Credit constraints and demand for higher education: Evidence from financial deregulation. *Review of Economics and Statistics*, 98(1), 12-24.

Figures

Figure 1: RD: Density Test and First Stage



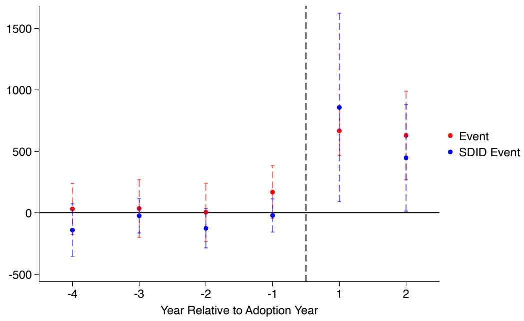
(a) FPL Density



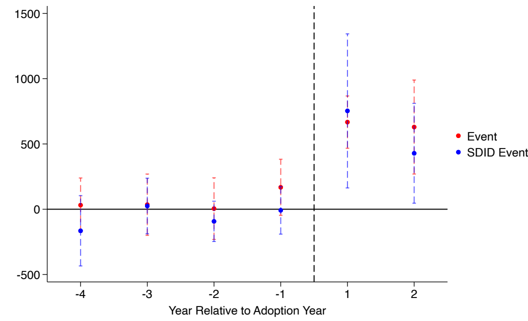
(b) G3 Receipt

Notes: Panel (a) displays a histogram of the assignment variable, FPL, with confidence intervals estimated using the local polynomial density estimator from Cattaneo, Jansson, and Ma (2020) at the FPL $\leq$ 400 assignment threshold. The density point estimate is 0.00023 (SE$=0.00021, p=0.99$). Panel (b) shows the probability of G3 grant aid receipt as a function of the FPL assignment variable, centered at 400. Bin width: 22, Sample: $\mid 1SD \mid$ of FPL.

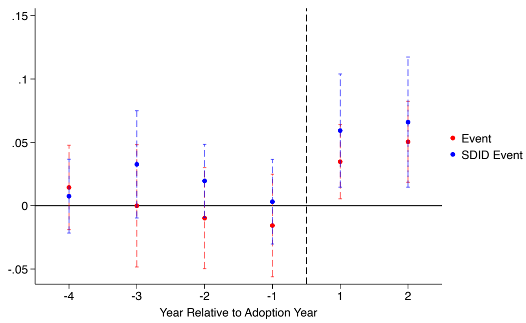
Figure 2: Event-Study Estimates of G3 on Financial Aid and Academic Outcomes



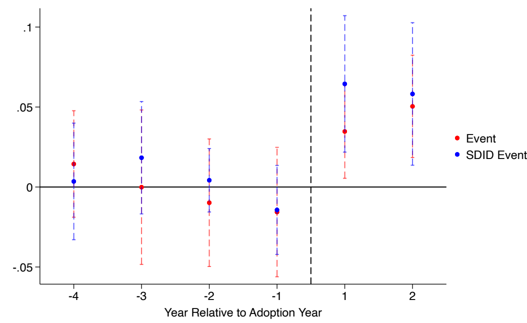
(a) Total Grant Aid



(b) Total Financial Aid



(c) Any Degree



(d) Certificate

Notes: The graphs display event-study point estimates and 95% confidence intervals from two designs estimating the effects of G3 on financial aid and academic outcomes: difference-in-differences (DID) and synthetic difference-in-differences (SDID). Outcomes include (a) total grant aid in year 1, (b) total financial aid in year 1, (c) any degree earned by year 2, and (d) certificate earned by year 2. The DID estimates are based on individual student observations (N = 96,187) and the SDID estimates are based on average outcomes at the school-by-year-by-G3 program eligibility level (N = 322).

Tables

Table 1: Summary Statistics for the Full Sample, FAFSA Completers, and RD-DID Sample

	Full Sample (1)	Completed FAFSA (2)	RD-DID Sample (3)
Demographic Characteristics			
Female	0.521	0.559	0.560
Asian	0.069	0.072	0.073
Black	0.185	0.222	0.223
Hispanic	0.157	0.163	0.164
White	0.505	0.462	0.460
Race: Missing	0.024	0.021	0.021
Age: 18-24	0.778	0.780	0.783
Age: 25-34	0.062	0.068	0.069
Age: 35 and over	0.045	0.038	0.035
0-200 FPL	0.367	0.554	0.559
200-400 FPL	0.184	0.278	0.281
Above 400 FPL	0.111	0.168	0.160
Enrollment			
Full time	0.648	0.710	0.710
Certificate	0.100	0.105	0.105
G3 Program	0.148	0.164	0.164
Health	0.073	0.085	0.085
Skilled Trades	0.058	0.060	0.060
Information Technology	0.181	0.182	0.181
Education	0.018	0.018	0.018
Public Safety	0.024	0.026	0.026
Financial Aid Outcomes			
Completed FAFSA	0.662	1.000	1.000
Received Grant Aid	0.565	0.816	0.822
Received G3	0.009	0.014	0.014
Received SSIG	0.008	0.012	0.012
Received Loans	0.118	0.176	0.175
Educational Attainment			
Earned Any Degree	0.150	0.170	0.169
Earned Certificate	0.088	0.100	0.099
N	174691	115627	113974

Notes: Full sample characteristics are for first-time-in-college (FTIC) Virginia community college students entering between 2016 and 2022. Income bands correspond to reported family income within 0–200%, 200–400%, and above 400% of the Federal Poverty Level (FPL). Column (2) includes only students who submitted a FAFSA. Column (3) includes the Regression Difference-in-Discontinuity (RD DID) sample consisting of students in 2016-2022 entry cohorts who completed the FAFSA and had a reported family income within 1000 percent FPL. G3 Program indicates whether students enrolled in a G3-eligible program. Any degree includes completion of a certificate, applied associate, or transfer-oriented associate degree within two years of entry. Certificate completion is also measures within two years of enrollment.
Abbreviations: Federal Poverty Level (FPL), Get a Skill, Get a Job, Get Ahead (G3), Student Support Incentive Grant (SSIG), First-Time-in-College (FTIC), Information Technology (IT).

Table 2: Reduced-form Difference-in-Discontinuity First-Stage and Baseline Balance

Dependent Variable	(1)	(2)	(3)	(4)
First Stage				
Received G3 Aid	0.779***	0.849***	0.976***	0.926***
	(0.024)	(0.023)	(0.025)	(0.034)
Baseline Covariate Balance				
Female	-0.068	-0.048	-0.014	-0.006
	(0.040)	(0.038)	(0.041)	(0.047)
Age	0.751*	0.341	-0.031	0.065
	(0.313)	(0.318)	(0.347)	(0.403)
Dependent	-0.017	0.001	0.015	-0.000
	(0.023)	(0.022)	(0.021)	(0.021)
Family Size	-0.035	-0.064	-0.022	-0.015
	(0.093)	(0.089)	(0.085)	(0.092)
White	-0.040*	-0.030	-0.032	-0.015
	(0.016)	(0.018)	(0.019)	(0.024)
Black	0.037*	0.020	0.024	0.026
	(0.015)	(0.015)	(0.016)	(0.016)
Hispanic	-0.010	-0.003	-0.007	-0.017
	(0.013)	(0.018)	(0.017)	(0.020)
Asian	0.011	0.008	0.011	-0.004
	(0.010)	(0.011)	(0.010)	(0.010)
Multiracial	-0.000	0.001	-0.001	0.004
	(0.012)	(0.013)	(0.016)	(0.017)
Race: Missing	-0.000	0.000	0.001	-0.002
	(0.006)	(0.007)	(0.007)	(0.012)
Bandwidth Restrictions	None	$\|FPL\| \leq$ 2SD	$\|FPL\| \leq$ 1.5SD	$\|FPL\| \leq$ 1SD

Notes: Each cell contains the result of a separate regression of the effect of I(FPL $\leq$ 400) interacted with an indicator for enrolling in a G3 program in the post-period (ITT=1) on G3 financial aid receipt and baseline attributes. Difference in discontinuity models estimate the reduce-form effect of G3 eligibility while conditioning on a placebo jump among students in non-G3 programs in the post-period and G3 and non-G3 students in the pre-period (i.e., a difference-in-discontinuity). All models include a linear spline of the forcing variable (FPL) unless otherwise noted, in which case a quadratic spline is included. Models include an indicator for FPL ≤ 0, and interactions of these regression discontinuity (RD) specification variables with a G3 program enrollment indicator. Additionally, all models control for institution by year fixed effects. FPL is centered at 400. Standard errors are reported in parentheses. (*p<.05 **p<.01 *** p<.001).

Table 3: Reduced-form Difference-in-Discontinuity Effect of G3 on Financial Aid Outcomes

	Difference in Discontinuity Estimates			
Dependent Variable	(1)	(2)	(3)	(4)
Total Grant Aid	1709.189***	1731.489***	2484.857***	2462.912***
	(176.927)	(168.376)	(148.986)	(152.720)
Mean	4174.87	4174.87	4174.87	4174.87
N	113,974	113,974	113,974	39,487
Total Financial Aid	1105.852***	1096.177***	1843.781***	1882.588***
	(194.265)	(193.192)	(173.467)	(183.941)
Mean	4985.66	4985.66	4985.66	4985.66
N	113,974	113,974	113,974	39,487
Loans	-603.338***	-635.312***	-641.076***	-580.325***
	(69.672)	(76.044)	(90.904)	(103.602)
Mean	810.79	810.79	810.79	810.79
N	113,974	113,974	113,974	39,487
Demographic Controls	No	Yes	Yes	Yes
Quadratic Spline	No	No	Yes	No
Bandwidth Restrictions	Full	Full	Full	$\|FPL\| \leq$ 1SD

Notes: Each cell contains the result of a separate regression of the effect of I(FPL $\leq$ 400) interacted with an indicator for enrolling in a G3 program in the post-period (ITT=1) on financial aid. The models estimate the reduce-form effect of G3 eligibility while conditioning on a placebo jump among students in non-G3 programs in the post-period and G3 and non-G3 students in the pre-period (i.e., a difference-in-discontinuity). All models include a linear spline of the forcing variable (FPL) unless otherwise noted, in which case a quadratic spline is included. Models include an indicator for FPL $\leq$ 0, and interactions of these regression discontinuity (RD) specification variables with a G3 program enrollment indicator. Additionally, all models control for cohort by institution fixed effects. FPL is centered at 400. Standard errors, clustered by institution and cohort year, are reported in parentheses. (*p<.05 **p<.01 *** p<.001).

Table 4: Reduced-form Difference-in-Discontinuity Effect of G3 on Academic Outcomes

	Difference in Discontinuity Estimates			
Dependent Variable	(1)	(2)	(3)	(4)
Degree, 2 years	0.056*	0.055*	0.051*	0.054*
	(0.024)	(0.024)	(0.024)	(0.027)
Mean	0.169	0.169	0.169	0.169
N	113,974	113,974	113,974	39,487
Certificate, 2 years	0.067**	0.065**	0.066**	0.051*
	(0.023)	(0.023)	(0.021)	(0.024)
Mean	0.099	0.099	0.099	0.099
N	113,974	113,974	113,974	39,487
Demographic Controls	No	Yes	Yes	Yes
Quadratic Spline	No	No	Yes	No
Bandwidth Restrictions	Full	Full	Full	$\|FPL\| \leq$ 1SD

Notes: Each cell contains the result of a separate regression of the effect of I(FPL $\leq$ 400) interacted with an indicator for enrolling in a G3 program in the post-period (ITT=1) on academic outcomes. The models estimate the reduce-form effect of G3 eligibility while conditioning on a placebo jump among students in non-G3 programs in the post-period and G3 and non-G3 students in the pre-period (i.e., a difference-in-discontinuity). All models include a linear spline of the forcing variable (FPL) unless otherwise noted, in which case a quadratic spline is included. Models include an indicator for FPL $\leq$ 0, and interactions of these regression discontinuity (RD) specification variables with a G3 program enrollment indicator. Additionally, all models control for cohort by institution fixed effects. FPL is centered at 400. Standard errors, clustered by institution and cohort year, are reported in parentheses. (*p$<$.05 **p$<$.01 *** p$<$.001).

Table 5: Difference-in-Discontinuity Estimates of G3 Effect on Outcomes with Bandwidth Restrictions

Dependent Variable:	Total Grant Aid (1)	Total Financial Aid (2)	Loans (3)	Degree, 2 years (4)	Certificate, 2 years (5)
Sample					
Full Sample, Linear Splines	1731.489***	1096.177***	-635.312***	0.055*	0.065**
	(168.376)	(193.192)	(76.044)	(0.024)	(0.023)
N	113,974	113,974	113,974	113,974	113,974
Full Sample, Linear and Quadratic	2484.857***	1843.781***	-641.076***	0.051	0.066*
	(234.841)	(235.051)	(103.072)	(0.031)	(0.029)
N	113,974	113,974	113,974	113,974	113,974
$\|FPL\| \leq 300$	2243.924***	1596.907***	-647.017***	0.057*	0.067**
	(186.037)	(178.044)	(90.412)	(0.028)	(0.025)
N	75,314	75,314	75,314	75,314	75,314
$\|FPL\| \leq 250$	2469.544***	1799.924***	-669.620***	0.058*	0.062*
	(202.334)	(209.085)	(97.972)	(0.028)	(0.028)
N	59,054	59,054	59,054	59,054	59,054
$\|FPL\| \leq 200$	2457.139***	1862.900***	-594.239***	0.040	0.045
	(198.801)	(222.179)	(101.343)	(0.033)	(0.031)
N	44,685	44,685	44,685	44,685	44,685
$\|FPL\| \leq 150$	2416.216***	1910.646***	-505.570***	0.065	0.054
	(202.022)	(242.774)	(117.204)	(0.039)	(0.036)
N	32,099	32,099	32,099	32,099	32,099
Kernel Weights	2388.347***	1886.201***	-502.146***	0.057	0.053
	(206.483)	(244.317)	(116.838)	(0.036)	(0.034)
N	41,688	41,688	41,688	41,688	41,688
CCT Optimal	2261.190***	1757.040***	-465.432*	0.064	0.069
	(326.265)	(344.908)	(194.950)	(0.037)	(0.037)
N	15,744	18,735	18,669	35,014	27,113
Demographic Controls	Yes	Yes	Yes	Yes	Yes

Notes: Each cell contains the result of a separate regression estimating the effect of I(FPL $\leq$ 400) interacted with an indicator for enrolling in a G3 program (ITT=1) on financial aid and academic outcomes.These models estimate the reduced form effect of G3 eligibility conditioned on a placebo jump for those students in non-G3 programs (i.e., difference-in-discontinuity). As such, all models include a linear spline of the forcing variable (FPL), an indicator for FPL $\leq$ 0, and interactions of these regression discontinuity (RD) specification variables with the G3 enrollment indicator. Additionally, all models control for cohort-by-institution fixed effects, inital program level, and a full set of baseline demographic characteristics, including student age, sex, race/ethnicity, dependency status, and family size. CCT refers to the Calonico, Cattaneo & Titunik (2014) optimal bandwidth and inference procedures. Kernel and CCT estimates utilize triangular kernels, while all other estimates apply uniform weights. FPL is centered at 400. Standard errors, clustered at the institution-by-cohort level, are reported in parentheses. (*p<.05 **p<.01 *** p<.001).

Table 6: Estimated Effects of G3 Eligibility on Student Demographic Characteristics

	DID Sample (1)	Full Sample (2)
Completed FAFSA	—	0.054***
		(0.011)
0-200 FPL	-0.026**	0.015
	(0.010)	(0.010)
200-400 FPL	0.026**	0.035***
	(0.010)	(0.007)
Above 400 FPL	0.000	0.004
	(0.000)	(0.005)
Age: 18-24	0.006	0.023*
	(0.009)	(0.011)
Age: 25-34	0.003	-0.004
	(0.008)	(0.006)
Age: 35 and over	-0.007	-0.016*
	(0.007)	(0.007)
Asian	0.007	0.009
	(0.007)	(0.006)
Black	0.037***	0.028**
	(0.010)	(0.009)
Hispanic	-0.012	0.001
	(0.008)	(0.004)
White	-0.035**	-0.040***
	(0.012)	(0.011)
Multiracial	0.009*	0.007*
	(0.004)	(0.003)
Race: Missing	-0.009**	-0.009**
	(0.003)	(0.003)
Female	-0.002	0.008
	(0.041)	(0.038)
N	96,187	174,691

Notes: Each cell presents results from a separate regression, with coefficients representing the estimated effect of G3 eligibility from the DID model. The sample consists of FTIC students from the 2016–2022 cohorts. The income-eligible DID sample includes students who completed the FAFSA and reported a family income below 400% of the Federal Poverty Level (FPL), while the full sample includes all FAFSA completers, regardless of income, as well as non-completers. All models include institution and entry cohort fixed effects. Standard errors, clustered at the institution-by-year level, are reported in parentheses. (*p<.05 **p<.01 *** p<.001).

Table 7: Panel-Based Estimates of the Effect of G3 on Financial Aid & Academic Outcomes

	Total Grant Aid		Total Financial Aid		Earned Any Degree		Earned Certificate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model Specification								
DID	592.673***	598.718***	539.946***	548.402***	0.049***	0.051***	0.048**	0.046***
	(107.547)	(109.589)	(111.595)	(117.327)	(0.013)	(0.013)	(0.014)	(0.013)
N	96,187	96,187	96,187	96,187	96,187	96,187	96,187	96,187
SDID	652.482*	706.735***	590.950*	603.907***	0.063	0.043	0.061***	0.032
	(258.752)	(156.203)	(289.933)	(134.883)	(0.033)	(0.024)	(0.017)	(0.025)
N	322	322	322	322	322	322	322	322
Includes Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Each column presents results from separate regressions using various panel-based estimators. All analytic samples consist of FTIC students from the 2016–2022 cohorts. The sample for the DID estimator is restricted to students who completed the FAFSA and reported an income below 400% of the Federal Poverty Level (FPL). For SDID models, data are aggregated at the institution-by-year-by-G3 program eligibility level. All models include entry cohort and institution fixed effects. Models with controls include race, gender, and age. Standard errors are clustered at the institution-by-year level. (*p<.05 **p<.01 *** p<.001).

8 Appendix A

Detailed Methodology

This appendix provides a comprehensive overview of the methodological approaches used. First we discuss the construction of the RD-DD estimand. And second we discuss the robustness checks in our panel-based estimation strategies and the assessment of G3 program impact.

Regression Discontinuity to Difference in Discontinuity

The cross-sectional RD in Eq. 3 can be estimated separately for different groups of students. For example, we can run the RD for (i) G3 students in the post-policy period, (ii) non-G3 students in the post-policy period, (iii) G3 students in the pre-policy period, and (iv) non-G3 students in the pre-policy period. Each of these regressions provides an estimate of the "jump" at the 400 percent FPL threshold for that group and period.

$$Y_i = \alpha + \beta I(FPL_i \leq 400) + f(FPL_i) + \boldsymbol{X}_i + \epsilon_i \tag{3}$$

where Y_i represents a series of financial aid and academic outcomes for student i, including G3 receipt, total grant aid, total financial aid (including loans), and degree or certificate completion within two years. The term $I(FPL \leq 400)$ is a binary indicator equal to one if reported family income falls at or below the 400 percent FPL threshold. The function $f(FPL)$ represents a smooth polynomial function of the assignment variable, allowing for flexibility in modeling the relationship between income and outcomes. The coefficient of interest, β, captures the discontinuous change in outcomes at the income eligibility threshold.

The RD-DD estimator combines these four estimates. First, we compare contemporaneous G3 students and non-G3 students, differencing out any discontinuities common to all students. Second, we compare these differences across periods, differencing out any pre-existing threshold effects. This two-step differencing isolates the causal effect of G3 eligibility at the threshold in the post-policy period.

In practice, rather than estimating four separate RDs, we implement this as a single pooled regression in Eq. 4 with a three-way interaction between the threshold indicator, G3 program enrollment, and the post-policy indicator:

$$Y_{ist} = \delta\big[I(FPL_i \leq 400) \times G3_i \times Post_t\big] + f(FPL_i) \times G3_i \times Post_t + \eta_{st} + \boldsymbol{X}_i + \epsilon_{ist} \tag{4}$$

The function $f(FPL_i)$ is interacted with group (i.e., G3) and period indicators so that all lower-order terms are included. Institution-by-cohort fixed effects η_{st} absorb mean differences across institutions and cohorts, including the main effect of $Post_t$. The coefficient δ is the RD-DD estimate: the change in the discontinuity for G3 students after G3 was introduced, relative to contemporaneous non-G3 students and to pre-policy cohorts.

Panel Based Estimators We employ multiple identification strategies to strengthen causal inference, including an event study framework, a triple-differences (DDD) approach, and a synthetic difference-in-differences (SDID) estimator. These methods allow us to assess the plausibility of key assumptions, address potential threats to internal validity, and refine our estimates of overall program effects. Below, we outline each approach in detail, beginning with the event study specification.

Event Study Estimates

A critical assumption for obtaining credibly causal estimates is that changes observed along program-ineligible students provide a valid counterfactual for treated students. We assess its plausibility using the following specification:

$$Y_{it} = \sum_{\tau=1}^{2} \delta_\tau G3_{i,t+\tau} + \sum_{n=0}^{4} \delta_n G3_{i,t-n} + \alpha_s + \epsilon_i t \tag{5}$$

where the coefficients δ_n and δ_τ capture the effect of participation in G3 for student i in cohort t, relative to students who never enrolled in G3-eligible programs. Specifically, δ_n represents the estimated effect for students who enrolled in G3 programs n entry cohorts prior, while δ_τ measures the effect for students who enrolled post-policy adoption in year τ. The reference category consists of students who never enroll in G3-eligible programs. To provide evidence in support of the parallel trends assumption, we test whether the pre-treatment cohort-to-cohort changes in outcomes among G3 students systematically differ from those observed among the comparison students. If we fail to reject the null hypothesis (H_0) of no differential pre-treatment trends, we interpet this as evidence consistent with the parallel-trends assumption.

Although G3 funds were only disbursed after 2021, variation in treatment timing in our context may be influenced by differing institutional practices regarding the timing of advertising and advising students about the G3 program, potentially leading to anticipatory effects. We also include a vector X' of student characteristics, such as reported race, gender, and age (see Table 1), following Roth et al. (2023), due to slight evidence of pre-treatment trend violations for some outcome variables see Appendix Table A3).

Triple Differences

To further understand the impacts of the G3 program, we include higher-income individuals and non-FAFSA completers in the model to estimate the DDD as follows:

$$Y_{it} = \theta(G3Aid_i) + P_{it}I_{it} + P_{it}T_t + I_{it}T_t + X_i'\beta + \epsilon_{it} \tag{6}$$

In equation 6, the additional indicator I_{it} represents whether a student was income-eligible for the G3 program. This term is interacted with entry cohort (T_t) and G3 program enrollment (P_{it}) to construct the counterfactual. The three-way interaction of income eligibility (I_{it}), G3 program enrollment (P_{it}) and enrollment post-policy adoption, represents the ITT effect of G3 financial aid, denoted as (θ).

The DDD strengthens casual inference by addressing three potential threats to internal validity. First, it accounts for broader time trends that could affect student outcomes during the G3 policy rollout by incorporating a never-treated group—income ineligible students—before and after policy implementation. Second, the DDD model controls for unobserved differences between groups that remain constant over time but may vary between G3 program enrollees and non-enrollees. Third, by adding an additional dimension—income eligibility—the DDD model controls for unobserved factors that could influence selection into the treatment, mitigating potential selection bias. While we include higher-income individuals and non-FAFSA completers in the model to estimate the DDD we also estimate results with higher-income individuals only (i.e., FAFSA completers) and find qualitatively similar results.

Synthetic Difference in Differences

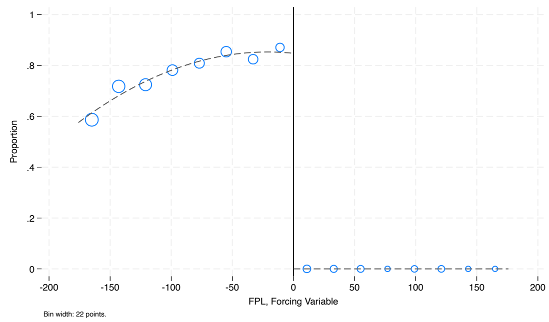
Unlike the synthetic control method, which is typically used for a single or small number of treated units, SDID accommodates a larger group of treatment units while incorporating institution and cohort fixed effects similar to a DID design. However, the SDID estimator also assigns weights to time periods, placing greater emphasis on pre-treatment periods that are most similar to the treated periods (Arkhangelsky et al., 2021; Clarke et al., 2023). By reweighting both units and time periods, SDID introduces a "double robustness" feature to the estimates, reducing the influence of potential specification errors and addressing threats to internal validity. This reweighting strategy can improve the precision of the estimates by removing systematic or predictable components of the outcome variable, particularly when there is sufficient heterogeneity in the outcome of interest (Clarke et al., 2023). Our SDID approach, incorporating this reweighting strategy, is specified as follows:

$$(\hat{\tau}^{SDID}, \hat{\alpha}, \hat{\beta}) = \underset{\tau,\alpha,\beta}{\operatorname{argmin}}\{\sum_{i=1}^{I}\sum_{t=1}^{T}(\bar{Y_{it}} - \alpha_i - \beta_t - T_{it}\tau)^2 * \hat{w_i}^{SDID} * \hat{\lambda_t}^{SDID}\} \tag{7}$$

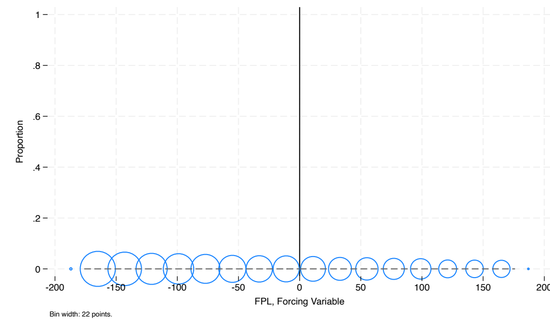
In this specification, $\bar{Y_{it}}$ represents the mean outcome for students at institution i in entry cohort t. Student participation in G3 in the period after its adoption is represented by $T_{it} \in [0, 1]$. The procedure requires a balanced sample of students at I institutions and T entry cohorts, so we average student outcomes and characteristics at the institution level. The main benefit of SDID is that the procedure optimally determines unit and time-specific weights ($\hat{w_i}^{SDID}$ and $\hat{\lambda_t}^{SDID}$), reducing reliance on the parallel trends assumption. The time period and institution fixed effects are represented by β and α, respectively. Following guidance from Clark et al. (2023), we also construct 95 percent confidence intervals using a block-bootstrap procedure and present SDID event-study estimates to further highlight pre- and post-policy adoption trends. This approach directly addresses the potential violations of the parallel trends assumption, improving the robustness and reliability of our findings. However, while SDID corrects for pre-trend violations, it does not eliminate bias from anticipatory impacts or compositional changes in the treatment group over time. To estimate the SDID model, a balanced panel is required. However, because individual students cannot be tracked across pre- and post-policy periods, we construct a balanced panel by averaging student outcomes and characteristics at the cohort-by-institution-by-G3 program eligibility level. Given this aggregation, the efficiency gains commonly observed in SDID models using student-level data are not present in our application.

Appendix Figures

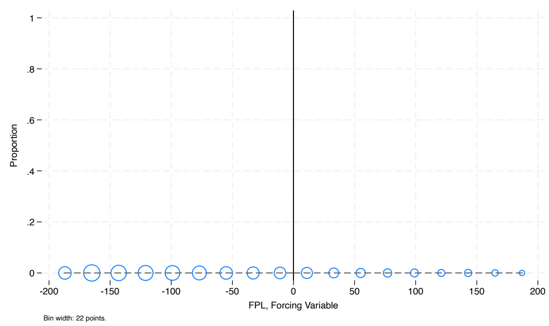
Figure A1: G3 Financial Aid Receipt by Sample



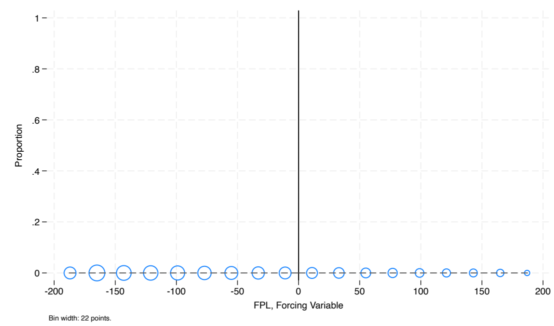
(a) G3 enrollees, Post-adoption



(b) Non-G3, Post-adoption



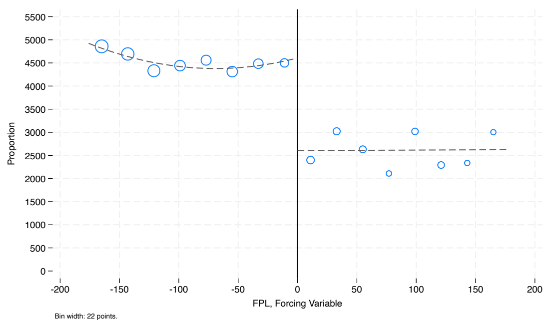
(c) G3 enrollees, Pre-adoption



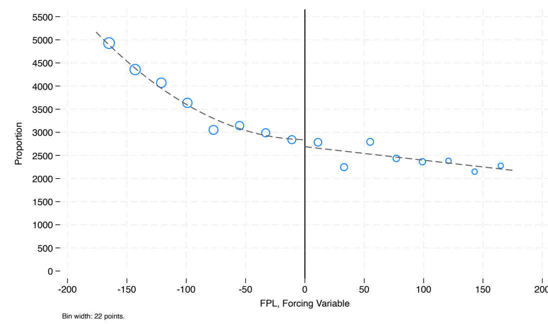
(d) Non-G3 enrollees, Pre-adoption

Notes: Each panel shows the relationship between baseline family income (percent of the federal poverty level, FPL) and receipt of G3 financial aid, separately by program type (G3 vs. non-G3) and period (pre- vs. post-adoption). Samples are restricted to students within one standard deviation of the FPL threshold, with bins of 20 FPL percentiles. Circles represent the bin-averaged outcome, weighted by the number of student observations. The dashed lines plot fitted regressions with separate splines estimated on either side of the eligibility threshold.

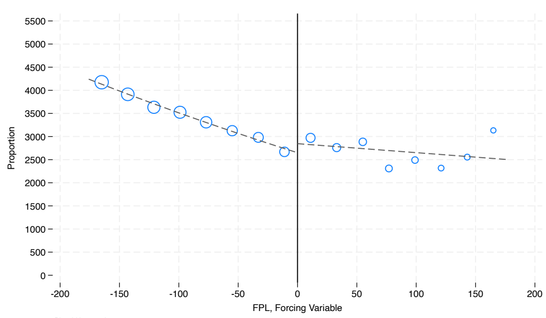
Figure A2: Total Financial Aid Received by Sample



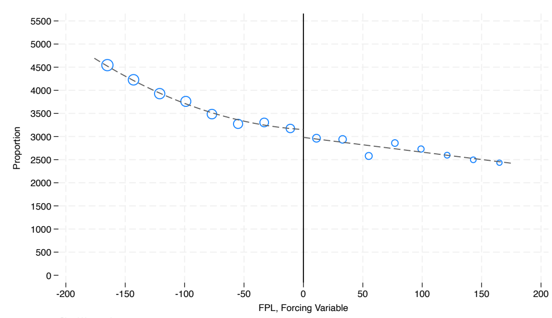
(a) G3 enrollees, Post-adoption



(b) Non-G3 enrollees, Post-adoption



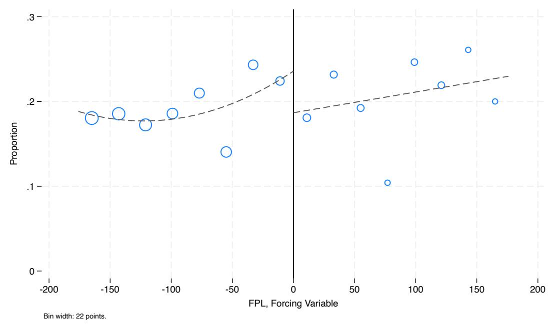
(c) G3 enrollees, Pre-adoption



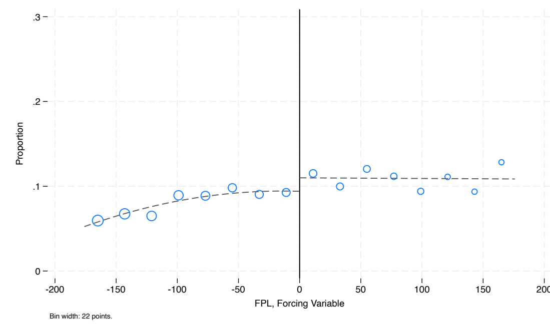
(d) Non-G3 enrollees, Pre-adoption

Notes: Each panel shows the relationship between baseline family income (percent of the federal poverty level, FPL) and total financial aid received, separately by program type (G3 vs. non-G3) and period (pre- vs. post-adoption). Samples are restricted to students within one standard deviation of the FPL threshold, with bins of 20 FPL percentiles. Circles represent the bin-averaged outcome, weighted by the number of student observations. The dashed lines plot fitted regressions with separate splines estimated on either side of the eligibility threshold.

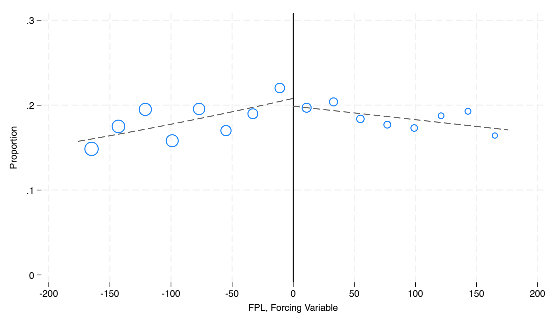
Figure A3: Certificate Completion by Sample



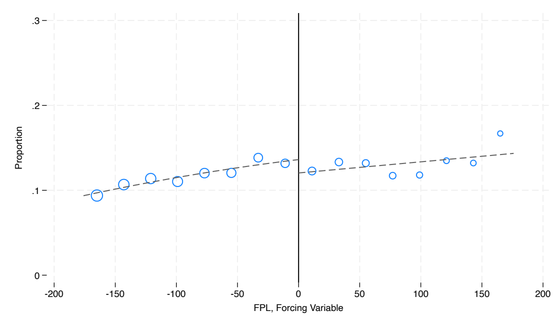
(a) G3 enrollees, Post-adoption



(b) Non-G3 enrollees, Post-adoption



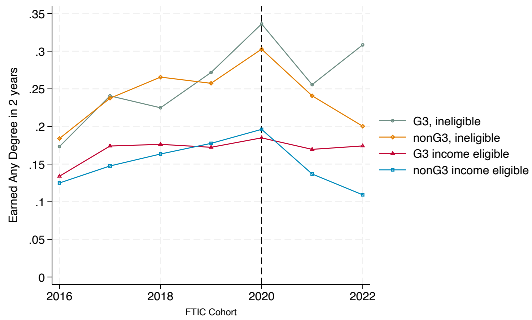
(c) G3 enrollees, Pre-adoption



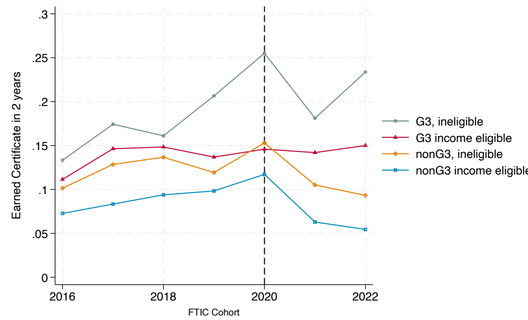
(d) Non-G3 enrollees, Pre-adoption

Notes: Each panel shows the relationship between baseline family income (percent of the federal poverty level, FPL) and certificate receipt by year 2, separately by program type (G3 vs. non-G3) and period (pre- vs. post-adoption). Samples are restricted to students within one standard deviation of the FPL threshold, with bins of 20 FPL percentiles. Circles represent the bin-averaged outcome, weighted by the number of student observations. The dashed lines plot fitted regressions with separate splines estimated on either side of the eligibility threshold.

Figure A4: Unconditional Credential Completion Rates, by G3 Program and Income Eligibility Status



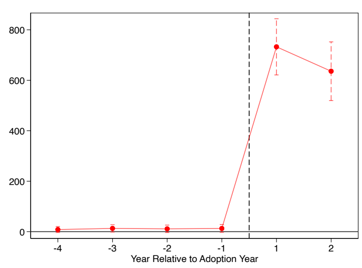
(a) Any Degree



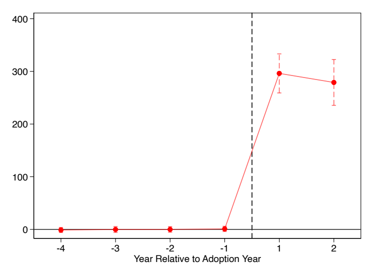
(b) Certificate

Notes: Figures depict unconditional credential completion rates on average by G3 program status and G3 income eligibility status over time. Any degree completion within 2 years includes associate degrees whereas certificates in two years do not include associate degrees. Students are deemed income eligible if they reported a family income within 400 percent of the federal poverty level. Students are considered G3 program eligible if they enrolled in a G3 eligible program. Accordingly, G3, ineligible indicates program eligibility but income ineligibility; nonG3, ineligible indicates program and income ineligibility; G3 income eligible indicates G3 income and program eligibilty; and nong3 income eligible indicates income eligibility but program ineligibility.

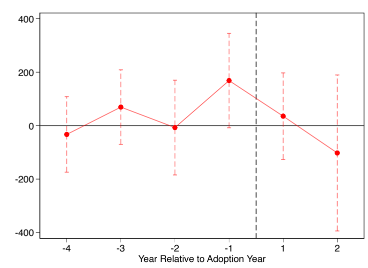
Figure A5: Event Study Estimates of Alternative Financial Aid Outcomes



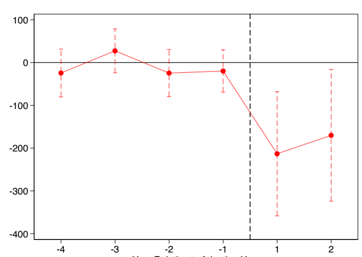
(a) G3 Aid



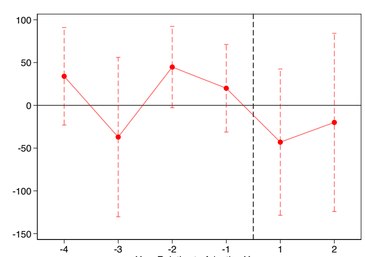
(b) SSIG Aid



(c) Federal Grant Aid



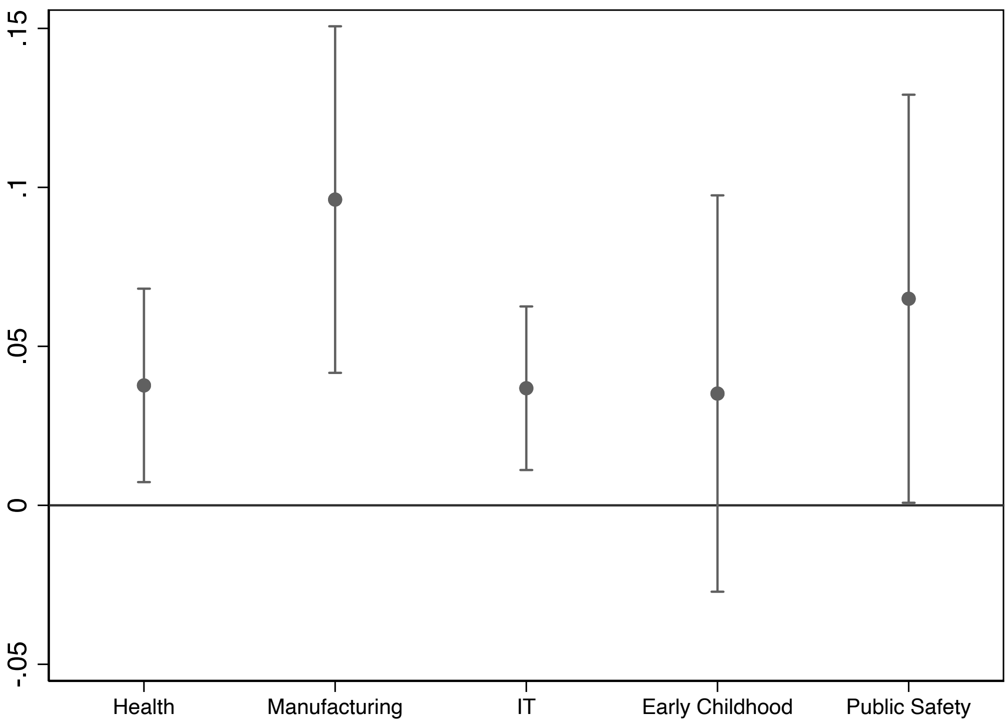
(d) State Grant Aid



(e) Institutional Grant Aid

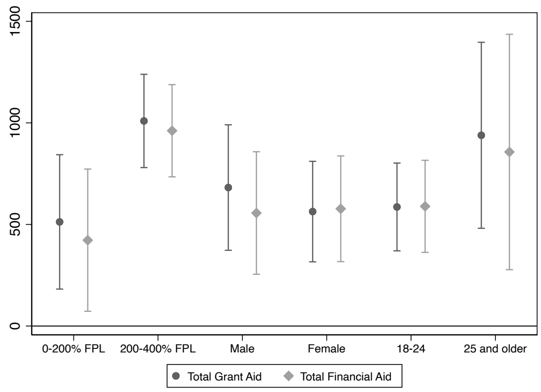
Notes: The graphs display event-study point estimates and 95% confidence intervals, estimating the effect of G3 eligibility on year-over-year changes in alternative financial aid outcomes. These exploratory outcomes include (a) G3 aid, (b) SSIG aid, (c) federal grant aid, (d) state grant aid, and (e) institutional grant aid. The sample consists of FTIC cohorts from 2016 to 2022 and includes only students who completed the FAFSA.

Figure A6: Estimated Effect of G3 on 2-year Certificate Completion, by G3 Program Area

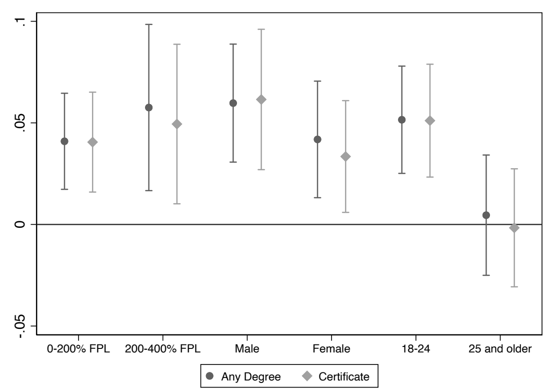


Notes: The graph displays point estimates and 95% confidence intervals from a difference-in-differences (DID) model estimating the effect of G3 eligibility on certificate completion within 2 years, by G3 program area. Analytic samples include FTIC cohorts from 2016 through 2022 and are limited to students who completed the FAFSA and had a reported income below 400 percent of the Federal Poverty Level.

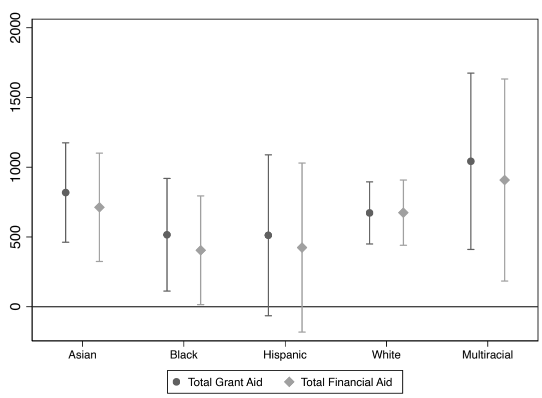
Figure A7: Effect of G3 on Financial Aid and Degree Completion from DID, by Student Subgroups



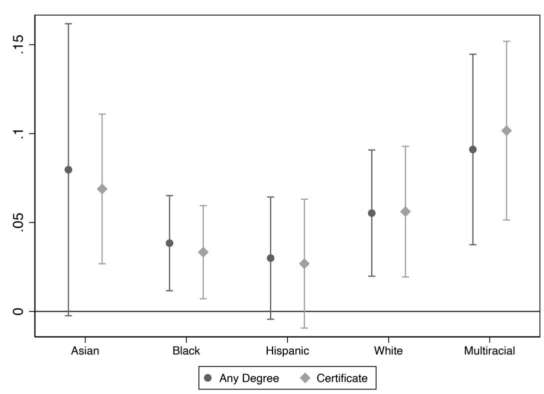
(a) Financial Aid, by Income, Gender, & Age



(b) Degree Completion, by Income, Gender, & Age



(c) Financial Aid, by Race/Ethnicity



(d) Degree Completion, by Race/Ethnicity

Notes: The graph displays point estimates and 95% confidence intervals from a difference-in-differences (DID) model estimating the effect of G3 eligibility on total grant aid, total financial aid, and degree and certificate completion within 2 years for each specified student subgroup. Analytic samples include FTIC cohorts from 2016 through 2022 and are limited to students who completed the FAFSA and had a reported income below 400 percent of the Federal Poverty Level.

Appendix Tables

Table A1: Reduced-form Difference-in-Discontinuity Effect of G3 on Additional Financial Aid Outcomes

	Difference in Discontinuity Estimates			
Dependent Variable	(1)	(2)	(3)	(4)
G3 Grant Aid	2657.517***	2659.475***	4054.192***	3696.636***
	(132.863)	(134.154)	(115.666)	(126.449)
Mean	34.10	34.10	34.10	34.10
N	113,974	113,974	113,974	39,487
Federal Grants	204.401	215.399	-280.667**	-99.127
	(115.355)	(110.067)	(86.062)	(62.673)
Mean	2973.78	2973.78	2973.78	2973.78
N	113,974	113,974	113,974	39,487
State Grants	-441.379***	-434.418***	-455.141***	-373.762***
	(76.537)	(71.736)	(52.536)	(55.622)
Mean	733.86	733.86	733.86	733.86
N	113,974	113,974	113,974	39,487
Institutional Grant Aid	-344.702***	-344.510***	-481.049***	-456.956***
	(81.682)	(85.022)	(46.656)	(61.151)
Mean	292.20	292.20	292.20	292.20
N	113,974	113,974	113,974	39,487
Demographic Controls	No	Yes	Yes	Yes
Quadratic Spline	No	No	Yes	No
Bandwidth Restrictions	Full	Full	Full	$\|FPL\| \leq$ 1SD

Notes: Each cell contains the result of a separate regression of the effect of I(FPL $\leq$ 400) interacted with an indicator for enrolling in a G3 program in the post-period (ITT=1) on extended financial aid. The models estimate the reduce-form effect of G3 eligibility while conditioning on a placebo jump among students in non-G3 programs in the post-period and G3 and non-G3 students in the pre-period (i.e., a difference-in-discontinuity). All models include a linear spline of the forcing variable (FPL) unless otherwise noted, in which case a quadratic spline is included. Models include an indicator for FPL $\leq$ 0, and interactions of these regression discontinuity (RD) specification variables with a G3 program enrollment indicator. Additionally, all models control for cohort by institution fixed effects. FPL is centered at 400. Standard errors, clustered by institution and cohort year, are reported in parentheses. (*p<.05 **p<.01 *** p<.001).

Table A2: Panel-Based Estimates of the Effect of G3 on FAFSA Completion and G3 and SSIG Award Amounts

	FAFSA Completion		G3 Aid		SSIG Aid	
	(1)	(2)	(3)	(4)	(5)	(6)
Model Specification						
DID	0.000	0.000	668.086***	671.163***	287.230***	287.372***
	(.)	(.)	(42.717)	(40.411)	(15.310)	(15.123)
N	96,187	96,187	96,187	96,187	96,187	96,187
Placebo	0.029*	0.022	0.000	0.000	0.000	0.000
	(0.014)	(0.012)	(.)	(.)	(.)	(.)
N	78,504	78,504	78,504	78,504	78,504	78,504
Triple DID	-0.040*	-0.036*	667.941***	670.392***	286.738***	286.989***
	(0.017)	(0.016)	(43.112)	(42.989)	(15.642)	(15.651)
N	174,691	174,691	174,691	174,691	174,691	174,691
SDID	0.024	0.000	501.310***	501.310***	196.846***	196.846***
	(0.013)	(0.000)	(109.394)	(109.394)	(21.716)	(21.716)
N	322	322	322	322	322	322
Includes Demographic Controls	No	Yes	No	Yes	No	Yes

Notes: Each column presents results from separate regressions using various panel-based estimators. All analytic samples consist of FTIC students from the 2016–2022 cohorts. The sample for the DID estimator is restricted to students who completed the FAFSA and reported an income below 400% of the Federal Poverty Level (FPL). In contrast, the placebo sample includes only students who either did not complete the FAFSA or reported an income above 400% of the FPL and were thus ineligble for G3 funds regardless of program enrollment. The Triple DID sample combines students from both the DID and Placebo samples. For SDID models, data are aggregated at the institution-by-year-by-G3 program eligibility level. All models include entry cohort and institution fixed effects. Models with controls include race, gender, and age. Standard errors are clustered at the institution-by-year level.
(*p<.05 **p<.01 *** p<.001).

Table A3: Event Study Estimates of G3 on Financial Aid and Academic Outcomes

	Total Grant Aid		Total Financial Aid		Any Degree		Certificate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lead 5	104.661	134.409	202.538	271.151*	0.007	0.004	-0.007	-0.008
	(96.063)	(85.617)	(129.150)	(132.345)	(0.016)	(0.017)	(0.017)	(0.017)
Lead 4	28.092	36.724	-8.627	31.381	0.021	0.016	0.017	0.014
	(106.088)	(99.568)	(109.105)	(105.325)	(0.020)	(0.020)	(0.017)	(0.017)
Lead 3	61.035	80.491	-19.440	34.826	0.004	-0.000	0.002	-0.000
	(122.675)	(112.028)	(127.290)	(118.791)	(0.028)	(0.027)	(0.025)	(0.024)
Lead 2	12.947	35.015	-57.691	4.727	-0.009	-0.014	-0.007	-0.010
	(97.551)	(100.427)	(115.637)	(119.502)	(0.017)	(0.017)	(0.020)	(0.020)
Lead 1	178.158	205.719	90.935	167.959	-0.009	-0.015	-0.013	-0.016
	(103.738)	(107.843)	(109.863)	(108.778)	(0.017)	(0.017)	(0.021)	(0.020)
Year 1	768.334***	783.315***	626.411***	667.338***	0.035*	0.035*	0.035*	0.035*
	(91.031)	(91.758)	(98.799)	(101.425)	(0.015)	(0.015)	(0.015)	(0.015)
Year 2	625.657***	613.578***	583.016**	629.615***	0.066***	0.062***	0.052**	0.050**
	(177.167)	(166.057)	(187.072)	(182.277)	(0.017)	(0.016)	(0.017)	(0.016)
F-statistic	0.707	0.948	0.838	1.247	0.406	0.462	0.362	0.364
p-value	.618	.451	.524	.289	.844	.804	.873	.872
N	96187	96187	96187	96187	96187	96187	96187	96187
Includes Demographic Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: These estimates come from an event study analysis examining the effects of G3 eligibility. The sample is limited to FTIC students from the 2016–2022 cohorts who completed the FAFSA and had a reported family income below 400% of the Federal Poverty Level (FPL). Each column presents results from separate regressions estimating dynamic effects over time. All models include program-level and institution fixed effects. Models with additional demographic controls account for race, gender, and age. Standard errors are clustered at the institution-by-year level. The reported F-test p-values assess the joint significance of Leads 1 through 5, testing the assumption that pre-treatment trends are equal to zero. (*p<.05 **p<.01 *** p<.001).

Table A4: Panel-Based Estimates of the Effect of G3 on Alternative Financial Aid Outcomes

	Federal Grant Aid (1)	State Grant Aid (2)	Institutional Grant Aid (3)	Other Grant Aid (4)	Federal Grant Aid (5)	State Grant Aid (6)	Institutional Grant Aid (7)	Other (8)
Model Specification								
DID	-66.489	-203.089***	-52.349	-40.716*	-78.662	-196.311***	-46.262	-38.582*
	(98.003)	(55.723)	(40.534)	(17.765)	(96.739)	(56.968)	(38.067)	(17.418)
N	96,187	96,187	96,187	96,187	96,187	96,187	96,187	96,187
Placebo	-5.610	26.048*	42.447	29.971	-5.886	24.697*	37.544	26.293
	(6.472)	(10.582)	(22.607)	(22.704)	(6.480)	(10.165)	(22.985)	(22.189)
N	78,504	78,504	78,504	78,504	78,504	78,504	78,504	78,504
Triple DID	-97.659	-241.059***	-105.748	-62.436	-91.439	-229.790***	-93.991	-56.523
	(135.801)	(62.574)	(73.771)	(39.707)	(133.175)	(62.755)	(73.014)	(39.549)
N	174,691	174,691	174,691	174,691	174,691	174,691	174,691	174,691
SDID	45.089	-13.894	-74.194	-17.984	85.153	-9.502	-84.018	-9.914
	(301.708)	(81.071)	(45.820)	(30.103)	(162.269)	(79.489)	(117.639)	(67.263)
N	322	322	322	322	322	322	322	322
Includes Demographic Controls	No	No	No	No	Yes	Yes	Yes	Yes

Notes: Each column presents results from separate regressions using various panel-based estimators. All analytic samples consist of FTIC students from the 2016–2022 cohorts. The sample for the DID estimator is restricted to students who completed the FAFSA and reported an income below 400% of the Federal Poverty Level (FPL). In contrast, the placebo sample includes only students who either did not complete the FAFSA or reported an income above 400% of the FPL and were thus ineligble for G3 funds regardless of program enrollment. The Triple DID sample combines students from both the DID and Placebo samples. For SDID models, data are aggregated at the institution-by-year-by-G3 program eligibility level. All models include entry cohort and institution fixed effects. Models with controls include race, gender, and age. Standard errors are clustered at the institution-by-year level.
(*p<.05 **p<.01 *** p<.001).

Table A5: Panel-Based Estimates of the Effect of G3 on Degree and Certificate Completion, among Students in Certificate Programs

	Earned Any Degree		Earned Certificate	
	(1)	(2)	(1)	(2)
Model Specification				
DID	0.073**	0.076**	0.065*	0.067*
	(0.027)	(0.025)	(0.028)	(0.026)
N	10,893	10,893	10,893	10,893
Placebo	0.031	0.028	0.027	0.025
	(0.022)	(0.022)	(0.022)	(0.022)
N	6,608	6,608	6,608	6,608
Triple DID	0.038	0.040	0.034	0.035
	(0.030)	(0.028)	(0.029)	(0.027)
N	17,501	17,501	17,501	17,501
SDID	0.088*	0.106**	0.077*	0.105**
	(0.039)	(0.038)	(0.037)	(0.039)
N	322	322	322	322
Includes Controls	No	Yes	No	Yes

Notes: Sample is restricted to students who first enrolled in a certificate program. Each column presents results from separate regressions using various panel-based estimators. All analytic samples consist of FTIC students from the 2016–2022 cohorts. The sample for the DID estimator is restricted to students who completed the FAFSA and reported an income below 400% of the Federal Poverty Level (FPL). In contrast, the placebo sample includes only students who either did not complete the FAFSA or reported an income above 400% of the FPL and were thus ineligble for G3 funds regardless of program enrollment. The Triple DID sample combines students from both the DID and Placebo samples. For SDID models, data are aggregated at the institution-by-year-by-G3 program eligibility level. All models include entry cohort and institution fixed effects. Models with controls include race, gender, and age. Standard errors are clustered at the institution-by-year level.
(*p<.05 **p<.01 *** p<.001).

Table A6: Placebo and Triple DID Estimates of the Effect of G3 on Financial Aid & Academic Outcomes

	Total Grant Aid		Total Financial Aid		Earned Any Degree		Earned Certificate	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Model Specification								
Placebo	92.857**	82.648*	133.093*	114.990*	0.030*	0.027*	0.028	0.026
	(34.681)	(33.899)	(55.866)	(52.127)	(0.014)	(0.013)	(0.015)	(0.015)
N	78,504	78,504	78,504	78,504	78,504	78,504	78,504	78,504
Triple DID	447.778**	485.638**	349.924*	358.866*	0.016	0.021	0.021	0.020
	(160.369)	(153.897)	(172.210)	(165.832)	(0.012)	(0.012)	(0.011)	(0.010)
N	174,691	174,691	174,691	174,691	174,691	174,691	174,691	174,691
Includes Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Each column presents results from separate regressions using various panel-based estimators. All analytic samples consist of FTIC students from the 2016–2022 cohorts. The placebo sample includes only students who either did not complete the FAFSA or reported an income above 400% of the FPL and were thus ineligble for G3 funds regardless of program enrollment. The Triple DID sample combines students from both the DID and Placebo samples. All models include entry cohort and institution fixed effects. Models with controls include race, gender, and age. Standard errors are clustered at the institution-by-year level.
(*p<.05 **p<.01 *** p<.001).