Innovative Higher Education
https://doi.org/10.1007/s10755-026-09900-w

Bridging the Gap: Evaluating the Impact of Summer Success Academy Bridge Program on College Success

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Received: 24 September 2025 / Accepted: 8 April 2026

Abstract
Given the large and persistent wage gaps between those with college degrees and those without, increasing the pool of college-educated workers remains a critical public policy objective. Many students–particularly those from lower-income households and those whose family members did not attend college–face numerous barriers to college entry and college success should they enroll. Therefore, efforts to help historically underserved students succeed in higher education hold considerable promise for expanding the pool of students attending and persisting in college. In this paper, we use regression-discontinuity analysis to examine one such program, called the Summer Success Academy (SSA). Using school administrative data from 2012–2017 to evaluate the impact of program participation on students' GPA and persistence in college, we find that participation in the SSA results in a significant positive effect on persistence, and that the effect is particularly strong for students who are eligible for Pell Grants. We do not find evidence that students in the program achieve higher grade point averages in college. The results suggest that even a relatively short summer support program can significantly improve persistence in college among historically underserved students.

Keywords Higher education · College access · Summer bridge program · Student supports · Student success · College readiness

The views expressed in this paper are the authors' and should not be interpreted as those of Georgia State University.

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Published online: 23 April 2026

Introduction

Many students, particularly those from lower-income households and those whose family members did not attend college, face numerous barriers to college entry and success (Bahr et al., 2023; Inkelas et al., 2007; Le et al., 2016; Li et al., 2024). Yet expanding access to four-year institutions for students with lower prior academic achievement raises important questions. Simply admitting more students risks higher dropout rates and wasted resources if students are unprepared for college-level work (Campbell & Campbell, 1997). Moreover, where students with lower test scores and GPAs should start college remains debated. Research suggests that beginning at a four-year institution may yield better outcomes than beginning at a two-year institution, particularly for students from lower-income households (Goodman et al., 2017; Pascarella & Terenzini, 1991). This creates a tension: should selective four-year institutions lower admissions thresholds and provide additional supports for historically underserved students, or does doing so compromise academic standards and institutional mission?

Summer bridge programs represent one response to this dilemma by attempting to expand access while maintaining success rates (Trogden et al., 2023; Williams et al., 2020). Evaluating whether such programs successfully navigate these competing pressures is therefore critical for students, administrators, and policymakers alike. In this paper, we examine one such program, operating at Georgia State University (GSU) in Atlanta, called the Summer Success Academy (SSA). More specifically, our research question is: do the structured supports provided through SSA during the summer improve student grade point average (GPA) and persistence at GSU, and do the effects differ by student gender and family resources? We examine GPA in students' first fall term and cumulative GPA at the completion of their first, second, third and fourth years, and persistence at GSU or graduation through one, two, three and four full years of attendance, as important indicators of student success in college.

The SSA program is unique in several ways. First, the university admits students with academic qualifications below the standard cutoff for acceptance, conditional on participation in the program during the summer before the fall semester of their freshman year. Second, the university uses standard admission criteria combined with predictive analytics to identify students who might benefit from the program, who are then offered conditional admission to the university. Third, the students enroll in standard for-credit courses rather than remedial or "catch-up" coursework. We find that participation in the SSA results in a significant positive effect on persistence at GSU, and that the effect is particularly strong for students who are eligible for Pell Grants. We do not find evidence that students in the program achieve higher grade point averages in college, though SSA students who are eligible for Pell Grants generally achieve GPAs that are statistically indistinguishable from their peers not in the program.

The next section reviews previous literature on similar initiatives, often called summer bridge programs, followed by additional details about the SSA itself. The third section provides an overview of the data, followed by a description of analytic methods, and the following section describes the results of our analyses. The paper concludes with implications and directions for future research.

Background and Literature Review

Literature Review

Summer bridge programs, interventions designed to facilitate students' transition from high school to college, have become relatively common across U.S. higher education institutions (Li et al., 2024; Liu et al., 2024). These programs typically aim to enhance students' academic preparedness, institutional integration, and retention rates (Bernacki et al., 2025). However, considerable variation exists across program structures, durations, and targeted student populations, complicating direct comparisons and generalization of findings.

A key structural distinction among summer bridge programs is whether participation is voluntary or mandatory. Most existing programs allow students to volunteer to participate, complicating efforts to estimate unbiased program impacts due to potential self-selection biases (Allen, 2001; Boyd & Green, 2020; Cross & Hicks, 2022; Haught, 1996; Wheatland, 2000). Existing literature suggests that voluntary programs enhance retention and performance, particularly for first-generation and underrepresented students (Cross & Hicks, 2022; Hermann et al., 2020; Palmer, 2018), although one study found no significant effect (Anthony & Schwartz, 2019).

A smaller number of programs mandate participation as an admission requirement (Gancarz et al., 1998; Maye, 1997; McMinn, 2004; Robert & Thomson, 1994; Stewart, 2006; Waller, 2009; Walpole et al., 2008). Although these programs share similarities with SSA in making full admission contingent upon participation, there are several differences. First, unlike other mandatory programs, SSA employs a clearly defined admission cutoff and predictive analytics to identify potential participants. Other programs, such as those studied by Stewart (2006), Gancarz et al. (1998), and McMinn (2004), do not have clearly specified admission criteria or cutoff scores. Second, while SSA conditions full admission solely on successful program participation, other mandatory programs typically impose stricter academic conditions, such as achieving a minimum grade (e.g., 'B' or higher), for students to secure formal admission.

Program lengths vary substantially, from brief four-day sessions (Fletcher et al., 2001) to more extensive programs spanning eight to ten weeks (Boyd & Green, 2020; Gancarz et al., 1998; Ghazzawi et al., 2022; McMinn, 2004). Unlike SSA, most summer bridge programs focus on remedial coursework designed specifically for participants (Gancarz et al., 1998; Logan et al., 2000; McMinn, 2004; Outlaw, 2008; Prather, 1996; Robert & Thomson, 1994; Stewart, 2006; Wheatland, 2000; Wolf-Wendel et al., 1999). These programs are commonly implemented at large, often urban, public universities serving diverse student populations, although variations exist across institutional contexts (What Works Clearinghouse, 2016).

Despite the widespread adoption of summer bridge programs, rigorous evidence supporting their effectiveness remains scarce. The What Works Clearinghouse (WWC) reviewed 137 studies on summer bridge programs, identifying only 31 as eligible for further analysis (What Works Clearinghouse, 2016). Among these, only one study (Murphy et al., 2010) met WWC research design standards, underscoring a dearth of methodologically rigorous research in this area. A common methodological limitation is the absence of valid comparison groups. Many studies rely on comparisons between program participants and non-participants, matched by demographic characteristics, a method insufficient for controlling for unobservable differences (Douglas & Attewell, 2014; Ghazzawi et al., 2022; Haugen, 2012; Malone, 2014; Outlaw, 2008; Palmer, 2018; Prather, 1996; Robert & Thomson, 1994; Stewart, 2006). Other studies, such as Gancarz et al. (1998) and McMinn (2004), compare students marginally below admission standards (conditionally admitted through summer bridge programs) to students marginally above the standards (regularly admitted) but use mean comparisons through ANOVA analyses rather than quasi-experimental designs.

The extant evaluations often focus on summer bridge programs' effects on historically underserved students. Several studies focus on students from lower-income households (e.g., Castles & Venters, 2022; Homel, 2013; Vergara et al., 2014; Yingling & Smith, 2018) and find positive and statistically significant effects on academic outcomes, particularly GPA (Castles & Venters, 2022; Homel, 2013); however, findings on persistence and retention remain mixed, with only Castles and Venters (2022) reporting significantly positive results, and others observing no statistically significant effects (Homel, 2013; Vergara et al., 2014). A smaller body of research addresses students with lower prior academic achievement, yielding inconsistent results. For example, Douglas and Attewell (2014) and Maye (1997) find positive academic outcomes, while three studies (Gancarz et al., 1998; McMinn, 2004; Stewart, 2006) find no significant effects. In addition, studies exploring intersections between socioeconomic and academic factors generally report positive outcomes among first-generations students and those from lower-income households (Allen & Bir, 2012; Appenzeller, 1998; Cabrera et al., 2013; Doerr et al., 2014; Robert & Thomson, 1994; Saenz & Barrera, 2007; Walpole et al., 2008).

While the literature often centers on traditional summer bridge programs focused on college transition and social and cultural integration, a more relevant analytical framework for the SSA emerges from studies of intensive, pre-matriculation interventions designed for remediation, such as the City University of New York's CUNY Start program. Unlike a conditional admission model, CUNY Start serves students who have already been accepted to the university but whose placement tests indicate the need for additional academic supports; these students then defer formal matriculation for a semester to receive intensive, low-cost instruction (Weiss et al., 2021). Evaluated through a rigorous randomized controlled trial, the program was found to substantially improve students' college readiness and modestly increase graduation rates, in part by creating a pathway to other comprehensive support programs (Weiss et al., 2021). While SSA's conditional admission model differs from CUNY Start's post-acceptance structure, CUNY Start's focus on providing students in a pre-matriculation cohort with integrated supports provides a highly relevant framework for understanding the potential impacts of GSU's program.

In summary, while the literature on traditional summer bridge programs shows mixed results, evidence from more intensive, pre-matriculation models like CUNY START suggests that a focus on academic remediation can yield positive outcomes. This highlights the importance of further investigation into how different program models produce differential impacts across demographic groups, particularly among students from lower-income households.

Summer Success Academy at Georgia State University

Initiated in 2012, the Summer Success Academy at Georgia State University aims to support students facing potential admission deferral or rejection (Georgia State Student Success Initiatives, n.d.-a; Renick, 2020) based on high school grades and standardized test scores. Georgia State serves one of the most diverse student bodies in the United States, with approximately 76 percent of students of color (41 percent Black and 13 percent Hispanic) and 51 percent of students receiving Pell Grants (University System of Georgia, 2023). Since the mid-2000s, GSU has received national recognition for its efforts to close achievement gaps by student race and ethnicity, income, and first-generation college-goer status (see, for example, Gumbel, 2020), so evaluation of one of its signature programs should be of broad interest to university staff and scholars.

Utilizing a weighted index of high school GPA and SAT or ACT scores—which we refer to as the Admission Index Review Criteria (AIRC)—as a pivotal component in admission decisions, the university generally defers or rejects students with an AIRC below a predetermined benchmark (Georgia State Student Success Initiatives, n.d.-b; Renick, 2020). The AIRC multiplies a student's high school GPA and SAT or ACT score by a constant and adds these numbers together to create a composite index that allows comparisons across students, taking account of both grades and standardized test scores. Note that the name Admission Index Review Criteria was created for this study and an additional constant was added to each student's score to protect confidentiality in the admissions process. The specific admission threshold has similarly been adjusted to account for this constant.

Since the SSA's inception, the university has also employed "predictive analytics" in addition to the AIRC to identify students who, despite a low AIRC, could potentially succeed in college with adequate support (Renick, 2020). These students are granted conditional full admission for the fall term, pending successful completion of the SSA program. While GSU adopted a test-optional admission policy in 2020, the AIRC served as the primary evaluative tool for assessing applicants during the 2012–2017 analysis period examined in this study.

The SSA takes place over a seven-week summer term, with students enrolling for seven credit hours. The courses include a required three-credit first-year writing course, a one-credit freshman orientation, and a three-credit elective chosen from the university's regular summer course offerings. Unlike remedial summer programs, the SSA enrolls students in regular summer classes alongside their peers.

In addition to academic coursework, the SSA integrates a range of support services, including tutoring, advising, financial literacy programs, academic skills workshops, peer mentors, and designated "Study Power Hours." All students participate in freshman learning communities and engage in community and campus projects, designed to enhance their sense of belonging and confidence, or "mindset" (Georgia State Student Success Initiatives, n.d.-a; Renick, 2020; Office of Admissions-Atlanta Campus, 2022).

The SSA supplemental services are funded by the university; academic departments pay instructional costs for the courses offered. Students in SSA pay tuition and fees, and for housing and meals when applicable, but are eligible for financial aid through Pell Grants and other sources.

Data and Methods

Data

The data used in the analyses come from administrative datasets maintained by GSU on all first-time applicants for the academic years 2012–2017. The dataset includes information on applicants' high school name and location, grade point average (GPA), SAT or ACT scores, AIRC, Pell Grant eligibility, demographic data (race and ethnicity, gender), and admission status, such as full admission, conditional admission, deferral, or rejection. For all students who enrolled at GSU, the dataset includes information on course-taking, grades, major, and enrollment status. We do not have post-high school information for students who did not enroll at GSU or data on enrollees after dropping out or transferring.

We restrict the sample used in the analyses in several ways. First, we include only students who enroll at GSU, as we have limited information on students who were rejected or chose not to enroll. Second, we exclude out-of-state students who would be less likely to enroll in a summer program that requires their physical presence. Third, we exclude student-athletes, as these students have other summer commitments and receive additional academic support not available to other students. Fourth, we remove students who participated in other academic support programs as first-year students. Next, we exclude students who applied for fall admission between May 15 and August 1, as these students' admission decisions would be too late to enroll in a summer program. We filter out rejected students in the admissions process, retaining only those accepted or conditionally accepted to GSU. Next, we narrow the sample further to include only students who attend in the fall immediately following their application cycle, as the summer bridge program takes place in the summer leading up to the start of their first year. These restrictions shrink the sample from 93,109 students to 21,882.

Table 1 presents descriptive statistics for the full sample of students enrolling as full-time first-time students at GSU, and for SSA participants and non-participants. Based on the results of independent two-sample t-tests, participants in SSA have significantly lower high school GPAs and standardized test scores than non-participants, as would be expected. Over half of each group is eligible for Pell Grants and

Table 1 Descriptive statistics of the full sample

	Variable	Full Sample $N=21{,}882$	SSA Participants $N=2{,}823$	Non-Participants $N=19{,}059$	SSA – Non-Part.ǂ
Means	AIRC (Index)	3264.25	2950.64	3310.70	−360.06*
	HS GPA	3.38	3.01	3.44	−0.43*
	SAT (V + M)	1066.58	947.22	1084.70	−137.48*
	ACT (V + M)	22.34	18.97	22.86	−3.89*
	% Pell Eligible	65.9%	74.5%	64.7%	9.8 ppts*
	% Female	57.8%	60.3%	57.4%	2.9 ppts*
	% White	29.0%	16.4%	30.8%	−14.4 ppts*
	% Black	40.6%	62.5%	37.4%	25.1 ppts*
	% Asian	18.8%	9.8%	20.1%	−10.3 ppts*
	% Others	8.2%	8.3%	8.1%	0.2 ppts
	% Hispanic	11.8%	10.0%	12.1%	−2.1 ppts*

The sample includes individuals who: 1) did not participate in other student assistance programs at GSU; 2) were not student-athletes; 3) were in-state applicants; 4) applied between August 1 and May 15; and 5) applied for the fall semester and enrolled in their application term

±Of 2,823 participants, 2,217 students had an Admission Index Review Criteria equal to or below 3000

ǂIndependent two-sample t-tests

*Group means significantly different at alpha < 0.05

Table 2 Descriptive statistics of the sample near 3000 AIRC (± 120.4 points)

	Variable	Full Sample N = 6,136	SSA Participants N = 2,113	Non-Participants N = 4,023	SSA – Non-Part.ǂ
Means	AIRC (Index)	3021.10	2964.62	3050.77	−86.14*
	HS GPA	3.08	3.02	3.11	−0.09*
	SAT (V + M)	983.72	954.33	999.62	−45.29*
	ACT (V + M)	19.90	19.11	20.34	−1.23*
	% Pell Eligible	71.8%	74.2%	70.6%	3.6 ppts*
	% Female	56.7%	58.1%	56.0%	2.1 ppts
	% White	22.0%	17.1%	24.6%	−7.5 ppts*
	% Black	54.4%	62.0%	50.5%	11.5 ppts*
	% Asian	11.8%	9.8%	12.9%	−3.1 ppts*
	% Others	8.3%	8.2%	8.3%	−0.1 ppts
	% Hispanic	11.4%	10.2%	12.1%	−1.9 ppts*

The sample includes individuals who: 1) did not participate in other student assistance programs at GSU; 2) were not student-athletes; 3) were in-state applicants; 4) applied between August 1 and May 15; and 5) applied for the fall semester and enrolled in their application term

±Of 2,113 participants, 1,664 students had an Admission Index Review Criteria equal to or below 3000

ǂIndependent two-sample t-tests

*Group means significantly different at alpha < 0.05

identifies as female and Black. Participants in SSA are substantially more likely to be Pell-eligible than non-participants, and to identify as Black, while non-participants are significantly more likely to identify as Asian, Hispanic, or White.

Most students in the non-participant group have an AIRC far from the threshold for eligibility, and so do not provide a strong comparison group for SSA participants. Therefore, Table 2 is limited to the sample of enrollees who meet the sample inclusion criteria and are within 120 points of the 3000 AIRC eligibility threshold for participation in the SSA. This sample includes 6,136 students. Column 1 shows that 71.8 percent of students in the sample qualify for need-based Pell Grants. Over half of students identify as Black, approximately 22 percent identify as White, 12 percent identify as either Hispanic or Asian, and 8 percent identify as other racial groups, such as multi-racial. Students' average high school GPA is 3.08, with average composite SAT scores of 983.7 and composite ACT scores of 19.9.

Column 2 displays descriptive statistics for the 2,113 students enrolled in the SSA, while Column 3 shows means for 4,023 students with an AIRC close to 3000 who did not enroll in the program. Column 4 displays the differences between the participants and non-participants, with results of bivariate independent samples difference of means t-tests for the two groups. By construction, the GPA and standardized test scores of students enrolled in the SSA are lower than for the full sample of enrollees. The demographic characteristics also show some significant differences, with students in the program more likely to be Pell-eligible and less likely to be White. The differences are particularly large for the percentage of Black students in

Table 3 SSA participants and non-enrollees near 3000 AIRC (± 120 points)

	Variable	Full Sample $N=6{,}223$	Enrolled & in SSA $N=2{,}113$	Not Enrolled at GSU $N=4{,}110$	Enrolled & SSA – Didn't Enroll‡
Means	AIRC (Index)	3006.65	2964.62	3028.26	−63.64*
	HS GPA	3.04	3.02	3.04	−0.03*
	SAT (V + M)	986.31	954.33	1003.58	−49.25*
	ACT (V + M)	20.07	19.11	20.60	−1.48*
	% Pell Eligible	57.9%	74.2%	49.5%	24.7 ppts*
	% Female	56.2%	58.1%	55.3%	2.8 ppts*
	% White	26.7%	17.1%	31.6%	−14.5 ppts*
	% Black	54.2%	62.0%	50.2%	11.8 ppts*
	% Asian	8.0%	9.8%	7.0%	2.8 ppts*
	% Others	8.1%	8.2%	8.1%	0.1 ppts
	% Hispanic	10.2%	10.2%	10.1%	0.1 ppts

The sample includes individuals who: 1) did not participate in other student assistance programs at GSU; 2) were not student-athletes; 3) were in-state applicants; and 4) applied between August 1 and May 15

‡Independent two-sample t-tests

*Group means significantly different at alpha < 0.05

each group. Based on academic qualifications and Pell-eligibility, students enrolled in the SSA could be expected to benefit from additional academic supports.

Because we have data on all applicants – not just enrollees – we can also compare the characteristics of applicants within 120 points of the 3000 AIRC who chose to enroll at GSU and attend SSA with those who did not enroll at GSU. As shown in Table 3, students who declined the offer of admission had similar GPAs to those who did enroll, but significantly higher SAT or ACT scores, based on independent two-sample t-tests. Non-enrollees are also significantly less likely to be eligible for Pell Grants and to identify as Black. While the comparison suggests that SSA participants differ in some important ways from the pool of students who chose not to enroll at the university, it does not indicate SSA participants would be more likely than those who declined the admission offer to succeed in college, based on observable characteristics.

Our key dependent variables of interest are students' first fall term (First Fall) GPA and cumulative GPA at the completion of their first, second, third and fourth years (inclusive of summer term). Similarly, we examine persistence at GSU through one, two, three and four full years of attendance.[1] To illustrate the temporal order of measurement, assume a student was enrolled in SSA during the summer of 2012.

[1] In this analysis, persistence is defined to include students who are either continuously enrolled or have graduated from this university in the given year. We employ this definition to avoid attrition bias, as not coding graduates as persisters would mean misclassifying the most successful student outcome as a negative one, thereby artificially depressing persistence rates.

The student's First Fall GPA is measured at the end of fall 2012, First Year GPA at the end of summer 2013, Second Year GPA at the end of summer 2014, and so forth. First-Year Persistence measures whether the student re-enrolled at GSU in fall 2013, Second-Year Persistence measures fall 2014 enrollment or graduation and so forth for each subsequent year.

Empirical Strategy

Our primary analytic strategy is a fuzzy regression-discontinuity design (RDD) comparing students near the 3000 AIRC threshold who enrolled in the SSA to those who did not. A sharp RDD would require perfect compliance with the assignment rule—all students below the 3000 AIRC threshold would participate in SSA and all students above would not. However, our data reveal imperfect compliance with this cutoff for several reasons. First, while the 3000 AIRC benchmark is the primary criterion, the university also employs additional predictive analytics and qualitative factors (not available to us as researchers) to determine program offers, such as grading standards at specific high schools with which admissions staff are familiar. Therefore, some students below 3000 may not receive be required to participate in SSA if other indicators suggest they would succeed without the program, while some students slightly above 3000 may receive an SSA offer if other factors indicate they would benefit, or may request to participate even if not initially selected. This imperfect compliance necessitates a fuzzy RDD approach, which uses the cutoff as an instrumental variable for program participation rather than assuming the cutoff deterministically assigns treatment.

Conceptually, the fuzzy RDD framework is best understood as a two-stage least squares (2SLS) model. The first stage models actual program participation (SSA_i) as a function of the cutoff rule and the running variable. The fitted values from this regression, denoted $\widehat{SSA}_i$, represent the predicted probability of participation. The second stage then uses these fitted values to estimate the causal effect on student outcomes. This approach can be represented with the following equations:

$$SSA_i = \gamma_0 + \gamma_1 BelowCutoff_i + \gamma_2 AIRC_{centered,i} + \gamma_3 (AIRC_{centered,i} * BelowCutoff_i) + X\prime_i \gamma_4 + \omega_i \tag{1}$$

$$Y_i = \beta_0 + \beta_1 \widehat{SSA}_i + \beta_2 AIRC_{centered,i} + \beta_3 (AIRC_{centered,i} * BelowCutoff_i) + X\prime_i \beta_4 + \varepsilon_i \tag{2}$$

In this framework, for student i, Y_i represents the outcomes of interest, such as GPA and persistence.[2] The dependent variable in the first stage, SSA_i, is an

[2] Persistence is defined as continued enrollment for the year at GSU, as we do not observe students once they leave the university. National Student Clearinghouse data tracking student enrollment from other institutions were not available for this study.

indicator for program participation, while $\widehat{SSA}_i$ in the second stage denotes the predicted probability of participation from the first stage. The running variable, $AIRC_{centered,i}$, is the student's AIRC score centered at the 3000 threshold. The key instrument, $BelowCutoff_i$, is a dichotomous variable equal to 1 if a student's AIRC score is below this 3000 cutoff and 0 otherwise. The interaction term, $(AIRC_{centered,i} * BelowCutoff_i)$, is included in both stages to allow the slopes of the running variable to differ on either side of the cutoff. Finally, the notation $X\prime_i\gamma$ denotes the inner product of the covariate vector and its corresponding coefficient vector, allowing multiple student background characteristics to be included simultaneously, while ω_i and ε_i represent the error terms in the first and second stages, respectively.

While these equations illustrate the conceptual parametric framework, our primary analysis employs a nonparametric local linear approach, following the recommendations of Gelman and Imbens (2019). Parametric models that use high-order global polynomials impose a specific functional form across the entire range of data. This can lead to "smoothing bias," where data points far from the cutoff disproportionately influence the estimated values at the cutoff. In contrast, the nonparametric approach focuses only on a local window of observations near the threshold. This minimizes smoothing bias by avoiding the assumption of a global functional form, while still flexibly allowing for different slopes on either side of the cutoff.

This design allows us to estimate the Local Average Treatment Effect (LATE) by treating the cutoff as an instrumental variable.[3] Given the fuzzy nature of the assignment, we further refine our estimation by incorporating a set of covariates—gender, race, ethnicity, and Federal Pell Grant eligibility—to help control for potential unobserved confounders, as recommended by Frölich and Huber (2017).

For bandwidth selection, we use the Mean Squared Error (MSE)-optimal selector from the rdrobust package (Calonico et al., 2020). This data-driven method balances the trade-off between bias and variance: selecting a bandwidth that is too wide introduces smoothing bias, while one that is too narrow reduces the effective sample size and increases variance. The MSE-optimal selector identifies the specific window that minimizes the combined expected error of the RD estimator. We calculate separate optimal bandwidths for GPA and persistence to ensure the analysis remains sensitive to the specific distribution of each outcome.

As RDD relies on sample sizes within specified bandwidths to analyze causal impacts, we conduct robustness checks to examine the sensitivity of our findings to variations in specification. First, we test the sensitivity of the results to different bandwidths by repeating the analysis with bandwidths set at half and twice the

[3] Unlike a standard two-stage least squares (2SLS) model, the nonparametric *rdrobust* package estimates the LATE as a single ratio of two discontinuities—the jump in the outcome divided by the jump in the treatment probability at the cutoff (i.e., a Wald estimator). Because it estimates these discontinuities in conditional expectations directly, rather than running a formal first-stage regression, it does not produce a first-stage F-statistic. Instead, the procedure computes the ratio directly, incorporating bias correction and robust standard errors.

optimal size. Additionally, we replicate our analyses using two other commonly utilized kernels—uniform and Epanechnikov—to ensure our results are not driven by specific kernel choices.

Analytic Results

An important assumption underlying regression-discontinuity analysis is that the running variable can accurately differentiate those who are offered a program from those who are not across the relevant threshold. The results of this analysis, estimated using a linear probability model (OLS) and shown in Table 4, confirm a key assumption of the RD design: there is a large discontinuity in the probability of SSA participation at the 3000 AIRC threshold. Enrollees with an AIRC below 3000 are 72 percentage points more likely to participate in the SSA than are students above 3000. The full sample, though, includes many students well above 3000 who would not be offered the program. Restricting the sample to students near the 3000 threshold (within 61.4 points above or below), students below 3000 are still significantly more likely (50.1 percentage points) to participate in the SSA. The control variables generally do not exhibit significant effects on participation rates; however, the results indicate that male students are somewhat less likely to participate, while Pell Grant-eligible students show a slightly increased likelihood of participation. Notably, Black students demonstrate a significantly higher probability of participating in the SSA, both within the full sample and the defined bandwidth. These findings suggest that AIRC serves as a strong, though not perfect, predictor of student participation in the SSA. Therefore, we use a fuzzy regression-discontinuity design to measure program effects.

A McCrary test (McCrary, 2008) indicates a statistically significant discontinuity in the density of observations, suggesting a "bunching" of students just above the 3000 AIRC threshold. However, we argue this result is unlikely to be driven by students precisely manipulating their scores to avoid the SSA requirement. The AIRC is calculated from a weighted average of cumulative high school GPA and standardized test scores, making it exceedingly difficult for students to finely tune their score to land just above a specific threshold. Furthermore, our data are from the early years of the SSA program when it was not widely known, making strategic behavior to avoid it improbable.

A more plausible explanation for the observed bunching is self-selection at the application stage. It is likely that some prospective students, aware of the general GSU admission standards, chose not to apply at all if they knew their score would be below the 3000 threshold. This would mechanically decrease the density of applicants just below the cutoff, creating the appearance of a relative excess of students just above it. Therefore, while the test is statistically significant, we interpret it as evidence of a selection effect in the applicant pool rather than score manipulation by admitted students. We are thus careful to infer the results of our analysis only to students who chose to apply and were willing to attend SSA as a condition of admission.

Table 4 Predicted probability of summer success academy participation

		Full Sample	Bandwidth =61.37
(Intercept)		0.483***	5.210***
		(0.022)	(0.922)
SSA Participation		0.720***	0.501***
		(0.005)	(0.0259)
AIRC		−0.000***	−0.002***
		(0.000)	(0.0004)
Male		−0.015***	−0.041***
		(0.003)	(0.0134)
Ref. = White	Black	0.023***	0.059***
		(0.004)	(0.0180)
	Asian	−0.001	−0.018
		(0.004)	(0.0251)
	More Than One Race	0.017**	0.099***
		(0.006)	(0.0273)
	Pacific Islander	0.098*	−0.081
		(0.048)	(0.377)
	Native American	−0.012	−0.133
		(0.028)	(0.135)
	No Response on Race	0.005	−0.014
		(0.009)	(0.0418)
Hispanic		−0.006	0.002
		(0.005)	(0.0236)
Pell Grant Eligibility		0.007*	0.010
		(0.003)	(0.0153)
N		21,882	3,284
R2		0.607	0.396
R2 Adj		0.606	0.394

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimates are from a linear probability model (OLS). The sample includes individuals who: 1) did not participate in other student assistance programs at GSU; 2) were not student-athletes; 3) were in-state applicants; 4) applied between August 1 and May 15; and 5) applied for the fall semester and enrolled in their application term

Baseline Model

Table 5 and Fig. 1 show the results of the regression discontinuity analysis examining program effects on students' GPA and persistence at Georgia State.

As shown in the top panel of Table 5 and in Fig. 1, we find no statistically significant effect of SSA participation on students' GPA during their first fall semester. However, for cumulative GPA in subsequent years, the estimated effects are consistently negative. By the end of the first year, SSA participants have a cumulative GPA that is significantly lower (−0.271 points) than that of non-participants. Across the second and third years, the effect fails to reach conventional levels of statistical significance, though the third-year estimate is negative and marginally significant. By

Table 5 Effects of summer success academy participation

		First Fall	Year 1	Year 2	Year 3	Year 4
Cumulative GPA	Bandwidth	78.264	75.092	120.394	75.199	83.488
	Treatment Effect (Std. Error)	0.145 (0.133)	−0.271* (0.123)	−0.065 (0.079)	−0.211† (0.109)	−0.368** (0.129)
	Conf. Interval	[−0.116, 0.405]	[−0.512, −0.029]	[−0.220, 0.090]	[−0.426, 0.003]	[−0.620, −0.116]
	Total # of Obs	3904	3224	3903	1919	989
	∟ SSA	1342	1085	1244	632	317
	∟ Non Participant	2562	2139	2659	1287	672
Persistence	Bandwidth		67.296	69.604	65.207	68.831
	Treatment Effect (Std. Error)		0.143* (0.057)	0.123† (0.073)	0.184* (0.079)	0.113 (0.074)
	Conf. Interval		[0.030, 0.255]	[−0.019, 0.266]	[0.029, 0.340]	[−0.033, 0.259]
	Total # of Obs		3533	3550	3505	3540
	∟ SSA		1222	1228	1220	1222
	∟ Non Participant		2311	2322	2285	2318

Significance levels are indicated by *** for $p<0.001$, ** for $p<0.01$, * for $p<0.05$, and † for $p<0.10$

All models use optimal bandwidth with a triangular kernel and include covariates for gender, race, ethnicity, and Pell grant eligibility. Graduating students are treated as having persisted in the graduation year and all subsequent years

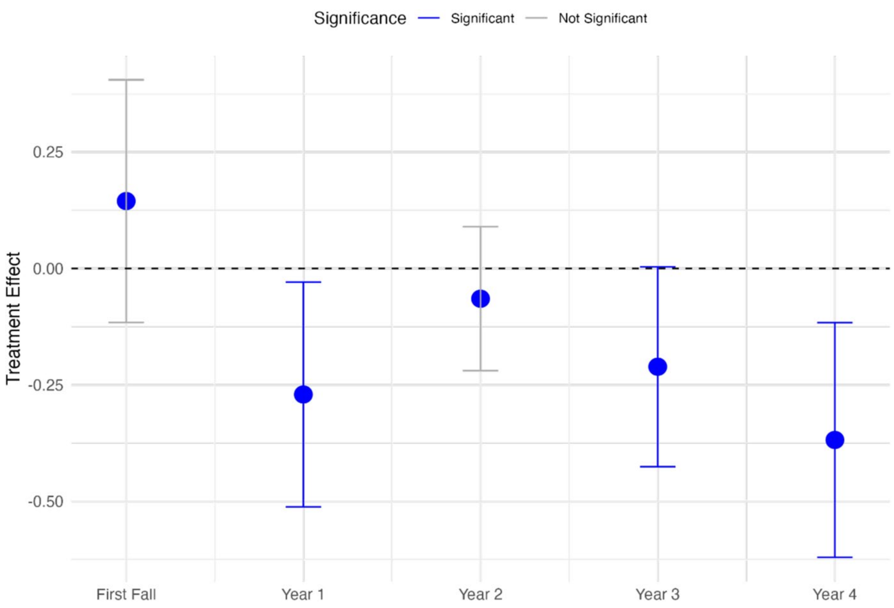

Fig. 1 Effects of SSA participation on cumulative GPA

the end of the fourth year, the negative effect is again statistically significant, with SSA participants' GPAs being 0.368 points lower than their counterparts.

The bottom panel of Table 5 and Fig. 2 show that students enrolled in the SSA are significantly more likely to persist or graduate throughout their first three years in

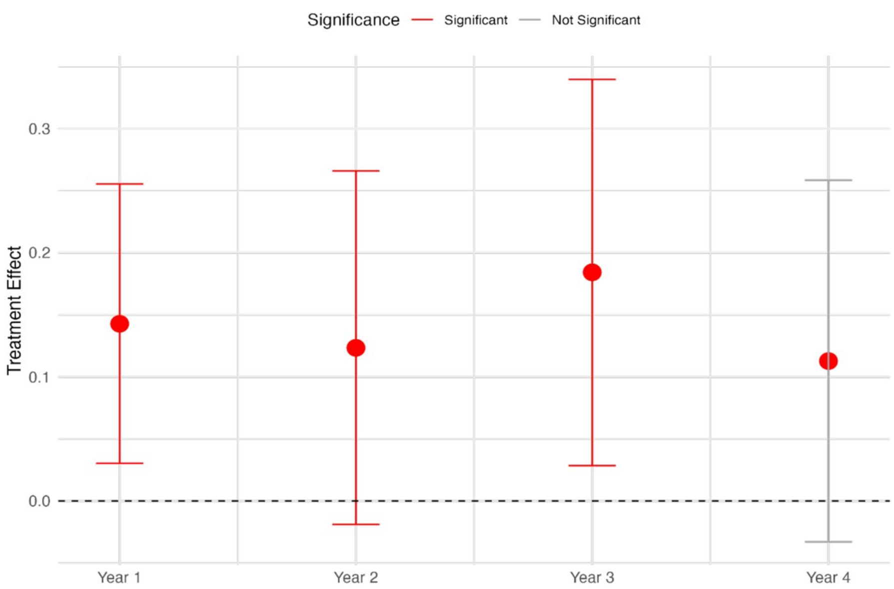

Fig. 2 Effects of SSA participation on persistence

Table 6 Effects of SSA participation on cumulative GPA by gender

		First Fall	Year 1	Year 2	Year 3	Year 4
	Bandwidth	78.264	75.092	120.394	75.199	83.488
Female	Treatment Effect (Std. Error)	0.0789 (0.187)	−0.493** (0.177)	−0.030 (0.108)	−0.125 (0.174)	−0.239 (0.162)
	Conf. Interval	[−0.289, 0.446]	[−0.840, −0.147]	[−0.242, 0.182]	[−0.465, 0.216]	[−0.556, 0.078]
	Total # of Obs	2210	1841	2317	1155	549
	∟ SSA	729	599	714	367	160
	∟ Non Participant	1481	1242	1603	788	389
Male	Treatment Effect (Std. Error)	0.155 (0.191)	−0.0727 (0.167)	−0.113 (0.113)	−0.304* (0.142)	−0.454* (0.195)
	Conf. Interval	[−0.218, 0.528]	[−0.399, 0.254]	[−0.335, 0.108]	[−0.582, −0.027]	[−0.836, −0.071]
	Total # of Obs	1694	1383	1586	764	440
	∟ SSA	613	486	530	265	157
	∟ Non Participant	1081	897	1056	499	283

Significance levels are indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$, and † for $p < 0.10$

All models use optimal bandwidth with a triangular kernel and include covariates for gender, race, ethnicity, and Pell grant eligibility. Graduating students are treated as having persisted in the graduation year and all subsequent years

Table 7 Effects of SSA participation on persistence by gender

		Year 1	Year 2	Year 3	Year 4
	Bandwidth	67.296	69.604	65.207	68.831
Female	Treatment Effect (Std. Error)	0.267*** (0.079)	0.104 (0.101)	0.191† (0.110)	0.0872 (0.103)
	Conf. Interval	[0.112, 0.422]	[−0.095, 0.303]	[−0.025, 0.407]	[−0.114, 0.289]
	Total # of Obs	1998	2006	1980	2000
	∟ SSA	662	666	662	662
	∟ Non Participant	1336	1340	1318	1338
Male	Treatment Effect (Std. Error)	0.0005 (0.084)	0.113 (0.103)	0.165 (0.113)	0.132 (0.107)
	Conf. Interval	[−0.163, 0.164]	[−0.089, 0.315]	[−0.058, 0.387]	[−0.078, 0.343]
	Total # of Obs	1535	1544	1525	1540
	∟ SSA	560	562	558	560
	∟ Non Participant	975	982	967	980

Significance levels are indicated by *** for $p<0.001$, ** for $p<0.01$, * for $p<0.05$, and † for $p<0.10$

All models use optimal bandwidth with a triangular kernel and include covariates for gender, race, ethnicity, and Pell grant eligibility. Graduating students are treated as having persisted in the graduation year and all subsequent years

college. Specifically, SSA participants are, on average, 14.3 percentage points more likely to complete their first year at GSU as compared to their counterparts who did not participate in the program. This higher persistence rate continues in subsequent years, with a difference of 12.3 percentage points as students complete their second year, and 18.4 percentage points through three years. The coefficient is positive but not significant through four years.

Robustness checks using different bandwidths and kernels (available upon request) present a consistent pattern with the effects of program participation on persistence through three years remaining positive and significant across all model variations.

Heterogeneity Analysis

In Tables 6, 7, 8, 9 and Figs. 3, 4, 5, 6, we analyze the effects of SSA on GPA and persistence, disaggregated by student gender and Pell Grant eligibility. The results in Table 6 and Fig. 3 show a significant negative effect on cumulative first year GPA for women, but no differences between participants and non-participants in subsequent years. For men, there are no significant differences until years 3 and 4, when participants have significantly lower cumulative GPAs than non-participants. It is important to note that the sample sizes in these disaggregated analyses are substantially smaller than in the full sample, leading to reduced statistical power and a higher likelihood of Type II (false negative) errors.

Table 8 Effects of SSA participation on cumulative GPA by pell grant eligibility

		First Fall	Year 1	Year 2	Year 3	Year 4
	Bandwidth	78.264	75.092	120.394	75.199	83.488
Pell-Eligible	Treatment Effect (Std. Error)	0.214 (0.149)	−0.165 (0.139)	0.0145 (0.089)	−0.0973 (0.122)	−0.284* (0.136)
	Conf. Interval	[−0.079, 0.507]	[−0.437, 0.108]	[−0.160, 0.189]	[−0.337, 0.142]	[−0.551, −0.017]
	Total # of Obs	2808	2339	2850	1421	775
	∟ SSA	969	779	898	475	249
	∟ Non Participant	1839	1560	1952	946	526
Non-Pell	Treatment Effect (Std. Error)	−0.0868 (0.279)	−0.635* (0.253)	−0.327* (0.161)	−0.741** (0.263)	−0.837* (0.343)
	Conf. Interval	[−0.634, 0.460]	[−1.130, −0.140]	[−0.642, −0.012]	[−1.257, −0.226]	[−1.509, −0.165]
	Total # of Obs	1096	885	1053	498	214
	∟ SSA	373	306	346	157	68
	∟ Non Participant	723	579	707	341	146

Significance levels are indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$, and † for $p < 0.10$

All models use optimal bandwidth with a triangular kernel and include covariates for gender, race, ethnicity, and Pell grant eligibility. Graduating students are treated as having persisted in the graduation year and all subsequent years

Table 9 Effects of SSA participation on persistence by pell grant eligibility

		Year 1	Year 2	Year 3	Year 4
	Bandwidth	67.296	69.604	65.207	68.831
Pell-Eligible	Treatment Effect (Std. Error)	0.120† (0.063)	0.0779 (0.080)	0.228* (0.089)	0.162† (0.085)
	Conf. Interval	[−0.004, 0.245]	[−0.079, 0.235]	[0.054, 0.402]	[−0.004, 0.328]
	Total # of Obs	2564	2578	2543	2569
	∟ SSA	896	902	894	896
	∟ Non Participant	1668	1676	1649	1673
Non-Pell	Treatment Effect (Std. Error)	0.198 (0.130)	0.212 (0.158)	−0.00258 (0.173)	−0.0614 (0.142)
	Conf. Interval	[−0.057, 0.454]	[−0.098, 0.522]	[−0.341, 0.336]	[−0.340, 0.217]
	Total # of Obs	969	972	962	971
	∟ SSA	326	326	326	326
	∟ Non Participant	643	646	636	645

Significance levels are indicated by *** for $p<0.001$, ** for $p<0.01$, * for $p<0.05$, and † for $p<0.10$

All models use optimal bandwidth with a triangular kernel and include covariates for gender, race, ethnicity, and Pell grant eligibility. Graduating students are treated as having persisted in the graduation year and all subsequent years

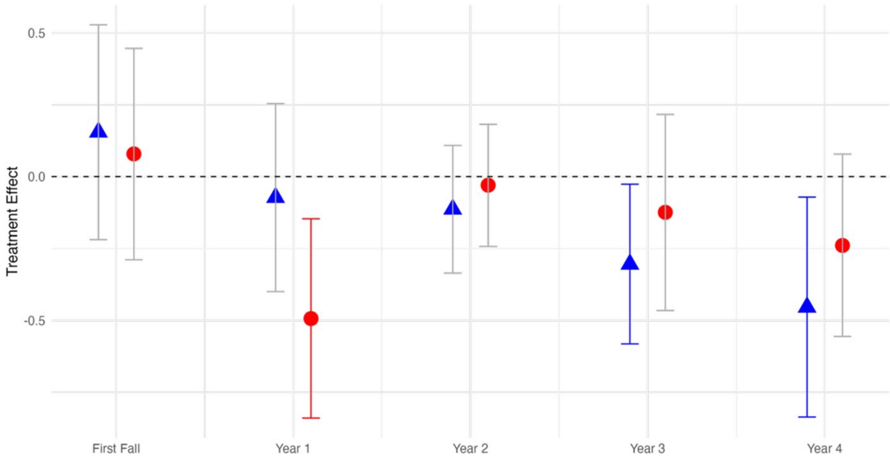

Fig. 3 Effects of SSA participation on cumulative GPA by gender

Table 7 and Fig. 4 display persistence results disaggregated by gender. The top panel shows a large and significant coefficient for first-year persistence among women, indicating that SSA participants are 26.7 percentage points more likely to persist at Georgia State through their first year as compared to non-participants. The

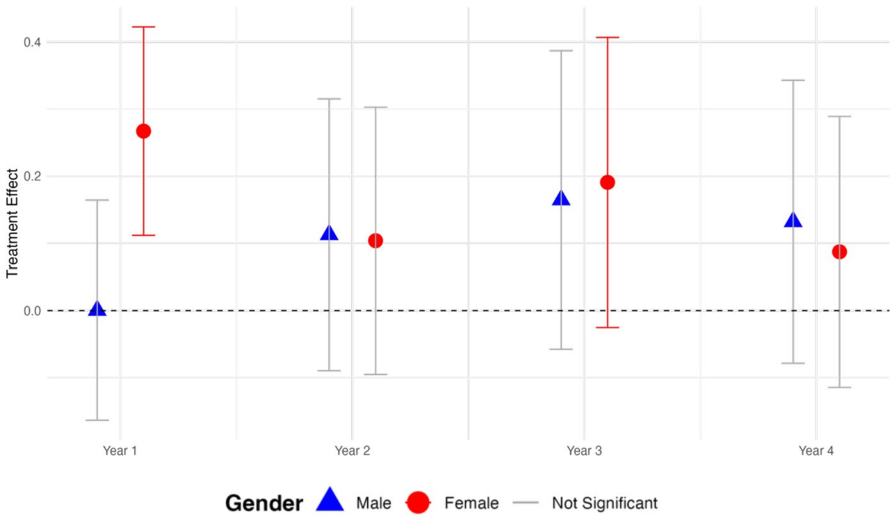

Fig. 4 Effects of SSA participation on persistence by gender

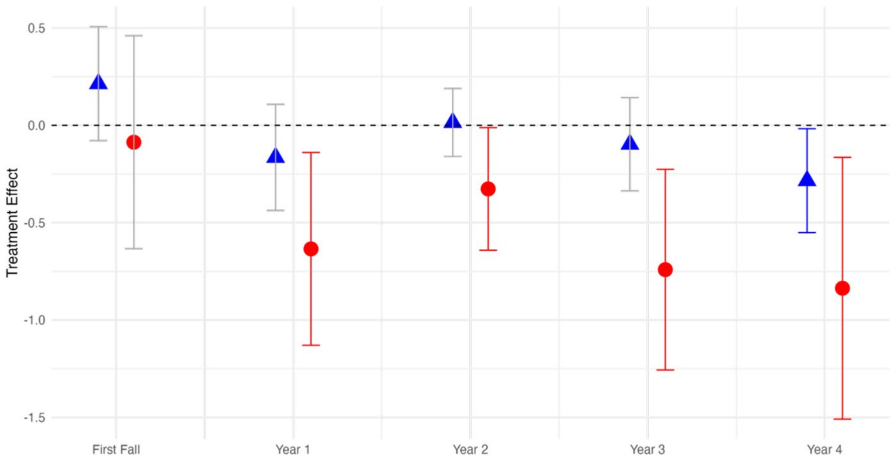

Fig. 5 Effects of SSA participation on cumulative GPA by pell grant eligibility

results in subsequent years are less consistent, with positive coefficients but a significant increase in persistence only in year 3. For men, there are no significant differences between participants and non-participants.

Tables 8 and 9 and Figs. 5 and 6 disaggregate results for students from lower-income households, as indicated by Pell Grant eligibility. As seen in Table 8 and Fig. 5, there are no significant differences for Pell-eligible students in GPA through

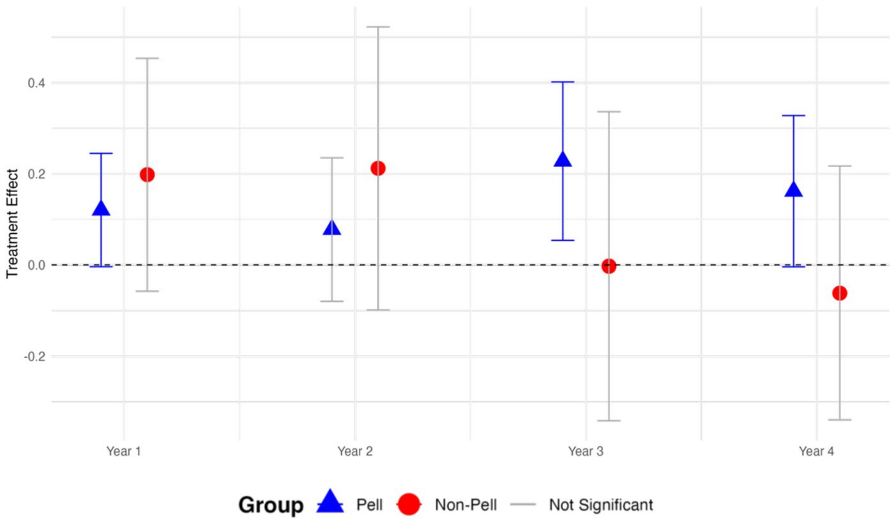

Fig. 6 Effects of SSA participation on persistence by pell eligibility

three years, with a negative effect in year 4. For students not eligible for Pell Grants, SSA participants have significantly lower cumulative GPAs in every year except the first fall term. By the fourth year the difference is fairly large (.837 GPA points on a four-point scale). Taken together, the results suggest that students in SSA achieve at similar levels to non-participants, but only for students from lower-income families.

Table 9 and Fig. 6 present results for persistence for Pell-eligible and ineligible students. For Pell-eligible students, SSA participants have significantly higher persistence rates than non-participants in every year except year two, in which the coefficient is positive but not significant. After four years, Pell-eligible SSA participants exhibit persistence rates 16.2 percentage points higher than Pell-eligible non-participants. For students not eligible for Pell grants, we find no significant differences in persistence rates between SSA participants and non-participants. Robustness checks using different bandwidths and kernels also find significant positive effects on persistence for Pell-eligible students, with no significant differences for students not eligible for Pell.

In sum, the heterogeneity analyses suggest that the overall patterns estimated with the full sample may mask important differences across groups of students, particularly students who are eligible for Pell Grants and those who are not (see also Winograd, 2025). We find that, overall, students who participated in the Summer Success Academy earn GPAs roughly equal to students who did not participate, while SSA participants persist or graduate at higher rates through three years of college. The persistence effects are particularly large for Pell-eligible students, suggesting that the program may help to reduce gaps in persistence between students based on family income.

Discussion

Findings

Using a regression-discontinuity design to compare college GPA and persistence rates for SSA participants to a group of similar non-participants with slightly higher high school qualifications, we find that participating in the SSA had a significant positive effect on students' likelihood of persisting at Georgia State or graduating. While the program did not lead to higher GPAs overall, it appeared to lead to a significant increase in persistence or graduation.

The effects were not uniform across all students. Students eligible for Pell Grants experienced the largest increases in persistence, suggesting that the program may be particularly effective for students from lower-income households who often face greater barriers to college success. This differential effect highlights both the program's potential for reducing degree attainment gaps and the importance of considering heterogeneous treatment effects in program evaluation.

Implications

These findings have several important implications for policy and practice. First, this analysis provides more rigorous evidence on summer bridge program effects than has generally been available in previous research. Unlike most studies of voluntary bridge programs, the SSA evaluation leverages a quasi-experimental design comparing students just above and below an admissions threshold, reducing concerns about self-selection bias.

Second, the results suggest that even a relatively short support program can significantly improve student persistence in college. The SSA participants would most likely not have been admitted to GSU without the program, indicating that there is, in fact, a pool of students who could succeed in college if admitted and given appropriate supports (see Williams et al., 2020). This challenges deficit-oriented perspectives that view lower test scores and GPAs as insurmountable barriers to college success.

Third, the program demonstrates a potentially cost-effective approach to expanding access. The supports do not require significant investments of new resources, particularly because they largely occur in the summer when there may be more available unused resources than during the academic year. The concentration of services in a brief, intensive period may also be more effective than spreading limited support across an entire academic year.

Finally, the particularly strong effects for Pell-eligible students suggest that such programs hold promise for reducing college degree attainment gaps. Given that students from lower-income households are often more likely to struggle in higher education, targeted programs like the SSA may be an important tool for promoting educational equity. The differential effects also suggest ways to further target recipient groups when resources are limited, potentially maximizing return on investment by focusing on students most likely to benefit.

Limitations

Several limitations of this analysis warrant attention. First, although we have several years of student-level data, they span the earliest years of the SSA. Early implementation challenges may have dampened effects, and the program may now be more effective than our estimates suggest.

Second, college graduation is one of the most important outcomes of the SSA and similar programs, yet we have data on four-year graduation only for a relatively small number of students who enrolled in the earliest program years, and no data on six-year graduation rates. Therefore, we have chosen not to present separate analyses of graduation effects to avoid presenting a potentially misleading picture of program outcomes. However, given that the likelihood of dropping out of college is highest earlier in students' college careers (Lee et al., 2024), higher persistence through the first several years may lead to higher eventual graduation rates.

Third, related to persistence, we can observe these outcomes only for students who stayed at GSU, so we cannot assess the program's effects on degree attainment for students who transfer to other institutions. If SSA participants are more or less likely to transfer than comparison students, our persistence estimates may not fully capture program effects on overall degree completion.

Fourth, although enrollment in the SSA is strongly related to students' incoming admission index, other unobserved factors also affected the university's decisions about whether to offer conditional admission to some students. The use of predictive analytics to identify potential students is an important feature of the program; however, additional data on the factors used to identify students for the offer could help refine future regression-discontinuity analyses.

Fifth, receiving an offer of admission conditional on enrolling in a summer program may cause some students to decline the offer and attend other schools or forego college. Our data do not allow us to track these students, so we cannot observe outcomes for those who were recommended for SSA but chose not to matriculate at GSU. Furthermore, students who accept the offer may be more motivated to attend GSU specifically or college in general. Therefore, we cannot infer that the program would improve persistence rates for any student receiving the offer, but more narrowly for students willing to participate in the summer program (Cordes, et al., 2025).

Sixth, our disaggregated analyses by Pell eligibility revealed important heterogeneous effects, but small sample sizes in some subgroups limited statistical power to detect effects. This particularly affects our ability to examine effects for other potentially important subgroups where sample sizes would be even smaller. The strong overall effects and clear patterns for Pell-eligible students provide confidence in our main findings, but readers should interpret null findings for other subgroups cautiously.

Finally, there is a bias-variance trade-off inherent in our estimation strategy. While the nonparametric approach reduces bias by focusing strictly on observations near the cutoff, it effectively reduces the sample size used for estimation. This trade-off results in larger standard errors compared to parametric models, implying that while our point estimates are less biased, they are estimated with less precision.

Recommendations and Future Research

These findings and limitations suggest several important directions for future research and practice. First, future evaluations should track longer-term outcomes, including six-year graduation rates and post-college outcomes such as employment and earnings. Understanding whether early persistence gains translate into degree completion and labor market success is essential for fully evaluating the program's value.

Second, research should attempt to track students who decline conditional admission offers or who transfer to other institutions. Understanding the full range of outcomes for students offered the program—not just those who participate at the original institution—would provide a more complete picture of program effects and help identify potential unintended consequences.

Third, future research could attempt to assess whether certain components of the program are particularly effective. The SSA includes multiple elements—early orientation, academic skill development, peer community building, and connection to support services—and it is possible that some components contribute more to positive outcomes than others. However, it is also possible that there is not a single "active ingredient" responsible for program effects but, instead, that the multiple components work together synergistically to improve student performance. Careful component analysis, perhaps using experimental variation in program elements, could inform more efficient program design.

Fourth, examining heterogeneous effects across a broader range of student characteristics, including race/ethnicity, first-generation status, and academic preparation levels, would help identify which students benefit most from the program. Such analyses would require larger samples but could inform more targeted and effective program recruitment and design. Understanding why Pell-eligible students benefit more than non-Pell students could also provide insights into program mechanisms.

Fifth, it will be important to see whether the SSA can be replicated at other institutions and in other contexts to produce similar effects. The program operates within Georgia State's specific institutional context, including its student population, resources, and support infrastructure. Replication studies would help establish the external validity of these findings and identify contextual factors that moderate program effectiveness.

Finally, institutions considering similar programs should carefully consider implementation details, including how to identify eligible students, how to structure conditional admission offers, and how to design summer programming that balances academic preparation with community building and motivation. The SSA's use of predictive analytics represents one promising approach, but institutions should also consider incorporating multiple measures of student potential beyond test scores and grades.

Conclusions

Providing appropriate support to students with lower prior academic achievement is a potentially important approach to expanding the pool of students who may be able to attend and succeed at four-year universities. While past efforts have often focused on requiring students to take developmental or remedial coursework, there has been increasing awareness of the potential negative consequences of this approach. Despite the costs for students and institutions, remedial or developmental courses have generally been shown to have small or negative effects on college outcomes, including persistence, credits attempted, and degree attainment, particularly for students at the margin of needing any remediation (Attewell et al., 2006; Boatman & Long, 2018; Calcagno & Long, 2008; Hodara, 2015; Martorell & McFarlin, 2011; Scott-Clayton & Rodriguez, 2015).

An alternative approach is to provide a menu of specialized supports, such as learning communities, assistance with time management and study skills, immediate enrollment in credit-earning coursework, and summer programs to help students acclimate and prepare for college life. In this paper, we analyze the effects of one such program that includes most of these elements, Georgia State University's Summer Success Academy. The SSA program is also unique in its use of predictive analytics to identify students who may benefit from the program and in making admission to the university conditional on participation in the program for some students who would not otherwise be admitted to the university as first-time freshmen.

The results of this analysis hold promise that, given an appropriate menu of supports, there are underserved students who could succeed in college if given the opportunity. The Summer Success Academy demonstrates that intensive, targeted intervention can help students with lower prior academic achievement persist and succeed at selective four-year institutions. As colleges and universities seek to expand access while maintaining student success, programs like the SSA offer a promising model worthy of further study and replication.

Acknowledgements This work utilizes data provided by Georgia State University. We thank the National Institute for Student Success for providing data and feedback, particularly Ben Brandon, Priscilla Bell, Romina H. Torres-Aranda and Tim Fulton, and Todd Jones for insightful comments on earlier drafts. The views and opinions expressed in this article are those of the authors and do not necessarily reflect the views or positions of Georgia State University.

Authors' Contributions JuneMi J. Kang and Ross Rubenstein both contributed to the conception and design of the study, the analysis and interpretation of the data, and the drafting and revision of the manuscript, and have read and approved the final manuscript.

Funding No funding was received for conducting this research.

Data Availability The data for this project are confidential and used with the permission of the National Institute for Student Success (NISS). Release of the data to a third party is prohibited unless permission is specifically granted by the NISS in writing.

Code Availability Access to code will be provided by corresponding author upon reasonable request and may be subject to the GSU's Internal Review Board (IRB) restrictions.

Declarations

Ethical Approval The Institutional Review Board of GSU approved the study (IRB # H19456).

Consent for Human Participants As the data used in this study consisted of de-identified administrative records, this study was deemed exempt from informed consent procedures.

Conflict of interest All authors declare that they have no conflict of interest in conducting this research.

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