Cutting the College Price TAG

The Effects of New Jersey's Tuition Aid Grant on College Persistence and Completion

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Preface

The state of New Jersey makes a significant investment in students through its Tuition Aid Grant (TAG) program. TAG addresses a social problem that is pervasive across the nation: lower rates of college completion among students who are less able to afford college. It is critical to understand how well the TAG program meets its goals of raising the college attainment of historically disadvantaged students and how the program might be improved in the future. To date, there has been no rigorous analysis of the outcomes of TAG recipients relative to other similar students who received less or no financial aid from the program.

New Jersey faces difficult trade-offs in structuring TAG. As TAG policy has developed under various constraints, the percentage of tuition covered by TAG has diverged across institutions. The eligibility formula is an imperfect measure of student financial need, potentially leaving gaps where students could benefit from additional funding. Given the different contexts of students across income levels and tuition charges at public, private, two-year, and four-year institutions, it is important to explore where the marginal dollar of TAG aid could have the greatest impact.

This research project addresses these questions using a new data set built by the New Jersey Higher Education Student Assistance Authority (HESAA). HESAA linked its administrative records to directory data from the National Student Clearinghouse. The data include eligibility and receipt of financial aid for the universe of TAG recipients, connected to college persistence and graduation over an eight-year period from 2012 to 2020.

We thank HESAA for their curiosity and cooperation. This project was funded by a grant from the ECMC Foundation. We appreciate feedback and comments from ECMC; the RAND Center for Causal Inference; RAND Education and Labor; and conference participants at the Association for Public Policy and Management, the Association for Education Finance and Policy, and the University of Wisconsin–Madison Interdisciplinary Training Program in Education Sciences. The report benefited greatly from peer review by Celeste Carruthers and Troy Smith. We thank Grace Gahlon for excellent research assistance.

About RAND Education and Labor

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Abbreviations

AICUNJ	Association of Independent Colleges and Universities of New Jersey
EFC	Expected Family Contribution
FAFSA	Free Application for Federal Student Aid
HESAA	Higher Education Student Assistance Authority
NJEI	New Jersey Eligibility Index
NSC	National Student Clearinghouse
TAG	Tuition Aid Grant

1. Meeting College Students' Needs Through Financial Aid

Higher education is a driver of social mobility, but access to college degrees is uneven and impeded by academic, social, and financial barriers (Chetty et al., 2017; Cohn, 2020; National Center for Education Statistics, 2019). Although communities and schools are innovating on several strategies to fight inequality in college completion, the response from state and federal governments has predominantly come in the form of financial aid for low-income students (Schneider and Clark, 2018; Pew Charitable Trusts, 2019). Government intervention is motivated by concerns of equity, that the direct benefits of college degrees should be more available to all, but also by efficiency. College degree holders grow the tax base through productivity and entrepreneurship, reduce health care costs, and are more likely to be informed and engaged citizens (Moretti, 2004; Dee, 2004; Lochner, 2011).

State and federal government decisionmakers face the challenge of directing limited financial aid dollars where they will meet students' needs and have the greatest impact on graduation rates (Lumina Foundation, 2020). The federal government's Free Application for Federal Student Aid (FAFSA) system has been the core model of assessing financial need, but states have developed different eligibility rules for applicants to their own financial aid programs (Chingos and Baum, 2017; Anderson, 2020a). Governments also face challenging decisions about how to fund these programs.

The COVID-19 pandemic has hit lower-income college students particularly hard (Aucejo et al., 2020). As of fall 2020, low-income students were twice as likely as high-income students to have canceled their fall enrollment in postsecondary education, and students canceling plans pointed to lost income as the reason more often than direct concerns about the coronavirus (U.S. Census Bureau, 2020). Enrollments decreased more steeply at community colleges, where lower-income students are more heavily represented, than at other institutions (National Student Clearinghouse Research Center, 2020). States might not be able to help, as their budgets for higher education are in jeopardy following the pandemic and recession (Yuen, 2020). Following a series of legislative proposals to expand the Pell Grant in smaller ways, a movement has emerged to double the size of the maximum Pell Grant with support from a coalition of colleges and universities, policy institutes, and the Democratic presidential platform (National Association of Student Financial Aid Administrators, 2020; Institute for College Access and Success, 2020; Biden, undated).

It is important for decisionmakers to draw on relevant research evidence to guide decisions about eligibility and expanded funding to achieve their equity and efficiency goals. Research tends to find positive effects of financial aid on persistence and completion (Nguyen, Kramer, and Evans, 2019; Page and Scott-Clayton, 2016), but the literature is fragmented. There is mixed evidence from randomized trials of private programs based on need (Angrist et al., 2014; Angrist et al., 2016; Anderson et al., 2019). The best evidence on large-scale public programs comes from natural experiments. Natural experiment study designs drill down to specific populations, affected by specific program rules, in specific colleges and years (we describe several examples below). Although these studies provide unbiased estimates of causal effects, their findings could be highly context-dependent. This is a classic trade-off. Researchers have opted for internal validity and bias minimization in the chosen sample at the expense of generalizability and applicability of estimates across samples.

As a result, answering practical questions such as "At which income levels is state financial aid most effective?" often requires comparing results across multiple programs, populations, and time periods. For example, in two studies of state aid supplementing the Pell Grant for low-income students, Castleman and Long, 2016, found that state aid significantly increased bachelor's degree completion for students with family incomes near $45,000 in 2020 dollars, while Gurantz, 2020, found no impacts of state aid for students with family incomes averaging $18,000 in 2020 dollars. Combining these estimates is unlikely to capture heterogeneity in the effects of financial aid by income alone, as the two studies focused, respectively, on the high school class of 2000 in Florida and on adult students who enrolled in California community colleges as late as 2011. Even studies within one state system demonstrate that subtle variations, such as the way a college presents loan offers, can make a difference in the effectiveness of financial aid (Marx and Turner, 2018; Park and Scott-Clayton, 2018).

Our study is unique in the literature in that we can hold more factors constant within one evaluation and potentially require less out-of-sample extrapolation to understand variation in effects. We focus on students in New Jersey, but the diversity of the state means that the study includes all types of colleges and universities and several student income levels. The design of the Tuition Aid Grant (TAG) creates several opportunities for natural experiments that apply similarly across contexts. We combine these mini-experiments in a cumulative multiple regression discontinuity approach that identifies the causal effects of financial aid.

TAG eligibility is determined by a continuous index based on household income and assets, and the grant amount increases in a stairstep-shaped function as this index falls. The jumps in TAG award amounts at the steps provide sharply different amounts of aid to individuals with otherwise similar backgrounds whose income and assets put them just above or below a key value of the eligibility index, creating the natural experiment described earlier. Assuming that there were no other unobserved differences across these individuals besides access to aid, we estimated the effects of the aid by tracking differences in their educational outcomes.

The nature of our data set, which is based on administrative records of TAG awards (rather than applications), focuses our analysis on already enrolled students during school years 2012–2013 through 2019–2020. Students in our data received from $1,000 to $13,000 per year in TAG awards, plus $600 to $6,000 per year in Pell Grant aid. Receiving increased TAG awards cuts the college price tag and often results in a larger check that students can take home to spend on living costs. The additional resources could help students to offset college expenses and to stay enrolled and work toward earning degrees.

We studied aid applications filed during seven school years to 52 colleges and universities included in our data, resulting in 1,920 discontinuities. In theory, all 1,920 effects could be estimated and ranked to find the types of students and schools where the TAG dollar goes furthest. In practice, those estimates would be too imprecise to be distinguished from each other or from no effect at all. To increase model precision, we grouped together students at similar points in their academic careers and at similar institutions.

Our analysis yielded mixed results. TAG effectiveness was most readily identified where there were large jumps in aid and a large number of students affected by those jumps, which was the case for students with lower incomes and those enrolled at public universities. Although we examined effects on year-to-year persistence and longer-term graduation, the largest impacts appear to have been on four-year degree completion.

We found that, on average, TAG aid increased the rate of on-time bachelor's degree completion at public universities. An additional $1,000 in aid led to a 2.6 percentage point increase in the graduation rate from a sample average graduation rate of 35 percent, a significant increase and higher than the average effect found in prior studies of other aid programs (Nguyen, Kramer, and Evans, 2019).

In community colleges and at private colleges and universities, the effect of TAG for its lowest-income recipients on four-year graduation outcomes was positive and marginally statistically significant.

For public university students, we could not reject the hypothesis that the effects of TAG were identical across the income levels served by the program. In other sectors, the estimates averaging across several income levels were imprecise and could not be statistically distinguished from no impact. A puzzling negative effect was estimated for on-time completion of bachelor's degrees at private institutions, though the negative effect faded at longer time intervals, suggesting that graduation was delayed. We discuss several potential reasons that eligibility for more TAG aid early in college could delay graduation for students who started at private colleges. TAG aid could crowd out other sources of aid, or aid could keep students enrolled at poorly matched colleges and delay graduation from any institution (Dillon and Smith, 2020).

In the following report, we provide additional details on the program, our data, and our strategy to estimate effects. We conclude by discussing the implications for New Jersey and other aid providers. The mix of results suggests that TAG aid, as currently delivered, might not be sufficient to overcome barriers of college affordability for many of its recipients. The positive effects on bachelor's degree completion show that delivering additional aid to lower-income college students, via the traditional state-federal methods of measuring financial need, can be a cost-effective way to support college attainment and reduce time to degree.

2. TAG Program and Data

The TAG program operates similarly to many other state programs, building on the widespread use of the federal aid system. This section elucidates what factors change the net price of college for a student, how the net price might change enrollment and completion outcomes, and how each of the stages generate data for evaluation. The section that follows this one describes TAG eligibility in more detail and how we used the structure of TAG and data from the state of New Jersey to estimate program effects.

Our study addressed three main research questions.

- How much does an additional $1,000 in TAG aid increase
    - short-term persistence: either graduating or re-enrolling for an additional year of college?
    - longer-term completion: graduation and/or transferring from a community college to a university?
- How do these effects differ across sectors: all students together, community colleges, public universities, and private nonprofit colleges and universities?
- How do these effects differ for students with the lowest incomes?

TAG is renewed each year. We therefore assessed the short-term effects of TAG aid received at any point in a student's college career, on persistence in that school year and the following fall. We also assessed longer-term effects of TAG aid received in a student's first year in college by focusing on beginning cohorts of students and tracking their graduation rates at different benchmarks.

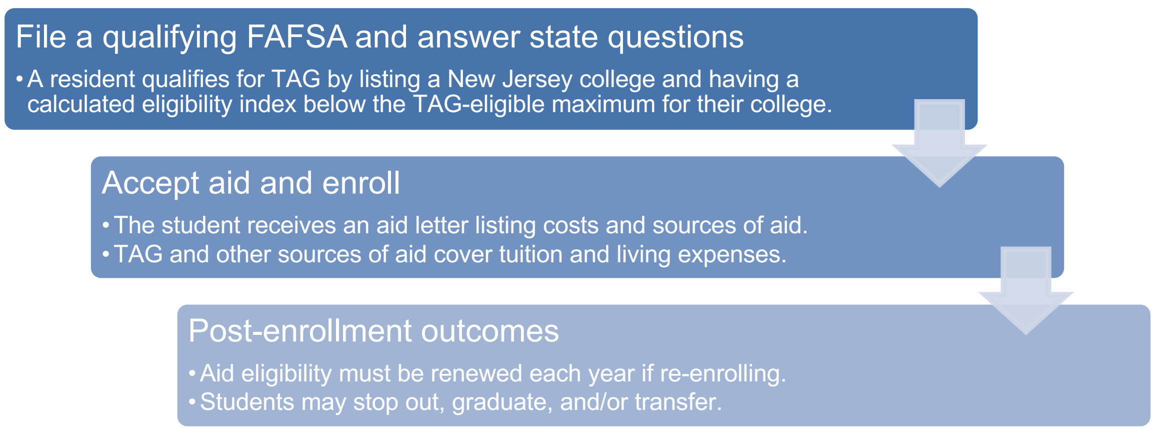
We additionally assessed whether there were differences in effects by income level and by college sector. The TAG program assigns larger amounts of grant aid for students with lower family incomes and for students facing higher tuition, which varies by college sector.

Financial Aid Process

Figure 2.1 shows the sequence of events that a student proceeds through during each school year. If the student is interested in receiving federal grants or loans, they must file the FAFSA. The FAFSA is an online form that can be prepopulated with information from tax returns. The federal government uses tax information, along with several other questions about the student's household, experiences, and college plans, to determine the student's eligibility for federal aid. The federal government then shares that FAFSA information with state officials in the student's home state and with the financial aid office at the student's college. To establish TAG eligibility during the period of our study, New Jersey required that the FAFSA be filed by specified deadlines and that students answer a few additional questions to complete their state record.[1]

The state calculates eligibility for TAG using the New Jersey Eligibility Index (NJEI), which is based primarily on household income. In combination with the college where the student enrolls, the NJEI determines the TAG award amount (this relationship is described in more detail in the next section). TAG can be used at all public and nonprofit private institutions in the state, as well as some academic degree–granting proprietary for-profit institutions, up to lifetime caps on semesters of eligibility.

Figure 2.1. Steps in Delivering Need-Based Financial Aid Through the TAG Program



During the enrollment process, the student's college financial aid office will present the student with an aid letter stating each charge and each source of aid. The sum of tuition, fees, and an estimate of living expenses constitutes the total cost of attendance. The cost of attendance, less all forms of financial aid, is the net price. It is common for a student to receive more aid than they must pay to the college to cover tuition and fee charges, and any federal aid beyond tuition and fees is paid out to the student to be used toward the remainder of the total cost.[2] The student can spend those funds on living expenses or other needs at their discretion.

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[1] The TAG deadlines occur just after the start of each semester for new students and in the spring before the school year starts for continuing students (HESAA, 2020c). The state questions were discontinued as of school year 2020–2021, but during our study period they were used to collect information on Social Security benefits, the Earned Income Tax Credit, Veterans Education Benefits, and other information. New Jersey also provides an alternative application for Dreamers (Deferred Action for Childhood Arrivals [DACA] program recipients) and undocumented students (HESAA, 2020d) that takes the place of both the FAFSA and state questions. Students can view their TAG eligibility within days after completing their state record, though eligibility could change upon receipt of new information during the process of verification, appeals, and professional judgments by financial aid officers.

[2] TAG, federal grants, other grants and scholarships, federal loans, and other loans are applied in that order. By rule, TAG aid is capped at the level of tuition, and total aid is capped at the total cost of attendance. In practice, neither of these caps reduce students' access to public grant aid: TAG awards are less than tuition for the institutions and years in this study, and total public grant aid (including the federal Pell Grant) is rarely more than the cost of attendance for TAG recipients.

The process in Figure 2.1 repeats each year that a student enrolls, and each year could bring changes in student eligibility, aid program design, and college prices. The TAG program therefore affects all types of students: beginning students, continuing students, and even prospective students who have never enrolled or who are considering returning to college.

The next two subsections build on Figure 2.1 to discuss the mechanisms by which differences in financial aid might affect decisions by TAG applicants at various stages (Figure 2.2) and how the financial aid process generates data for evaluation (Figure 2.3). The figures all display the same three steps in the process, which occur sequentially during each school year.

Figure 2.2. Prospective Student Decisionmaking at Each Step

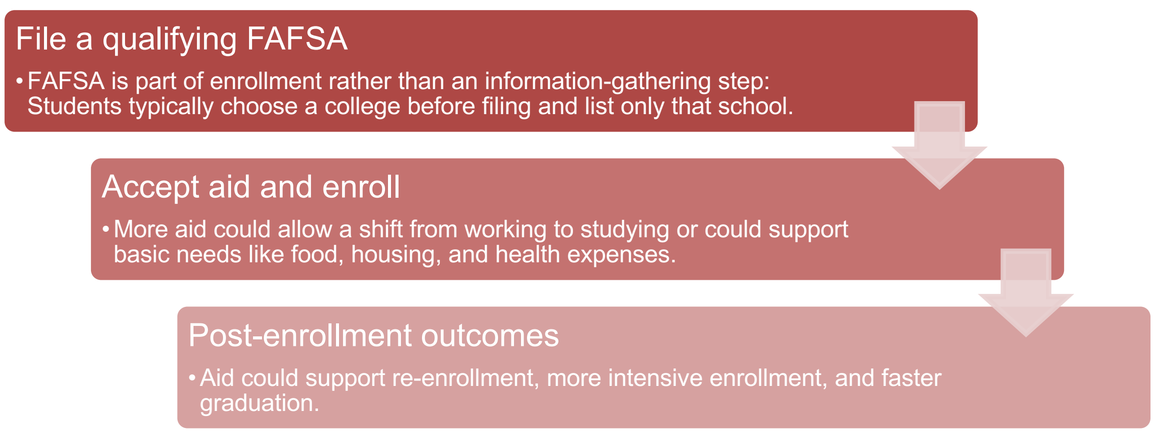
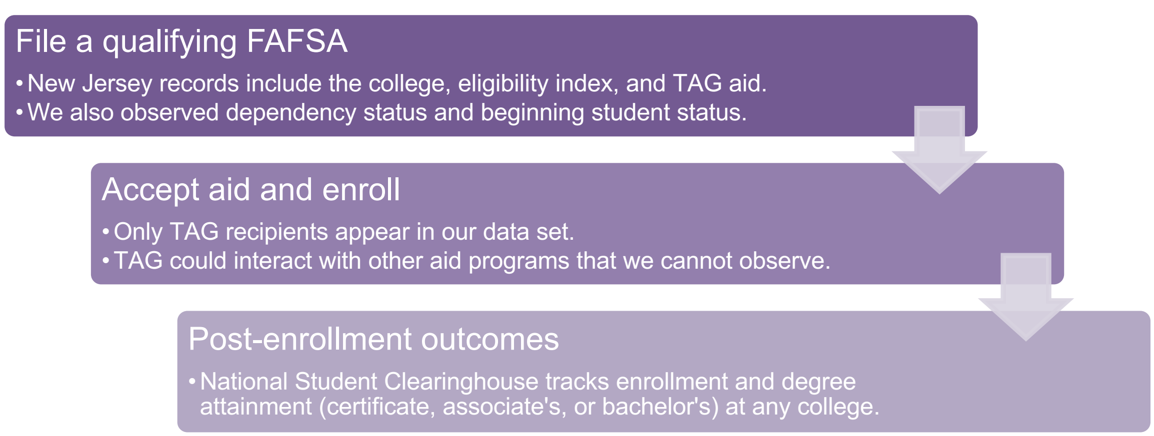


Figure 2.3. Data Collection at Each Step



The Potential Effects of Financial Aid

Thinking about how students make college choices within the framework of Figure 2.1 might bring to mind a student optimizing over several dimensions: where to apply, where to enroll, and what to study. Ideally, a student would gather information up front about the net price as an input to this optimization process. However, this scenario only represents a small fraction of the college enrollment decisions made by today's students (Avery and Hoxby, 2004). Most students who are applying for aid are already enrolled at a college, and they are deciding whether to persist and how to pay for it. Others entering college for the first time do not appear to use the FAFSA process to compare prices across colleges: Students commonly list only one institution or, in some cases, a few institutions from the same sector, such as two local community colleges (Anderson, 2020a; Gurantz, 2020; Porter and Conzelmann, 2017).

Students entering college clearly pay attention to some concept of price on the margin (Deming and Dynarski, 2010; Denning, 2017; Acton, 2020). However, the way that state need-based aid affects the net price is hard for students to see or predict until they have committed the time and effort to apply to a particular college, chosen their credit load, applied for financial aid, and settled their aid package with the college. The uncertainty means that small variations in net price are unlikely to affect major decisions like whether to enroll in college or which college to choose, and this is borne out in prior research (Carruthers and Welch, 2019; Castleman and Long, 2016; Denning, Marx, and Turner, 2019). Thus, we expect that the primary opportunities for TAG aid to affect students' choices arrive after they enroll and receive the aid each year.

In the short term, receiving more aid potentially loosens financial constraints. Aid could allow a shift from working to studying (Broton, Goldrick-Rab, and Benson, 2016). Aid could support basic needs like food, housing, and health, which present challenges for many college students (Baker-Smith et al., 2020; Broton, 2020; Leung at al., 2020). Additional grant aid could lower the need to borrow, which for some students carries a high psychological cost (Walsemann, Gee, and Gentile, 2015). Supporting expenses through grant aid could therefore increase the likelihood that a student will persist in college. Early accumulation of credits was a key indicator of persistence for aid recipients studied by Angrist, Autor, and Pallais, 2020.

Over the longer term, these investments could compound and make students more likely to earn degrees and earn them sooner (Hossler et al., 2009). Longer-term follow-up at different time points yielded changing results in two randomized evaluations of need-based aid programs. Effects of aid that first appear positive might fade over time (Angrist et al., 2014; Angrist et al., 2016; Anderson et al., 2019). That fade suggests that the group initially receiving less aid caught up to the group initially receiving more aid. Degree effects can also differ by sector and coverage of costs. Goldrick-Rab et al., 2016, and Anderson et al., 2019, found that substantial aid given to university students had positive effects increasing on-time completion of bachelor's degrees, while smaller amounts given to community college students had no discernible effect.

In general, public need-based grants can have muted or negative effects if they do not loosen financial constraints. Aid that covers a small portion of costs might not help many students overcome financial barriers. There could be other program interactions that make additional TAG aid less likely to increase financial resources, such as when a student who received more in TAG aid then receives less grant or scholarship aid as a direct consequence. This phenomenon of public aid crowding out institutional discounts is prevalent for the Pell Grant (Turner, 2017). Crowd-out can occur at private colleges and universities as they seek to use limited financial aid budgets to attract and retain students (National Association of College and University Business Officers, 2020). At community colleges in New Jersey, students now receive "last dollar" state aid from a different grant program to fully cover tuition after Pell Grants and TAG are applied (HESAA, 2020b). Both of these mechanisms are more likely to affect moderate-income students who have less of their costs covered by public grant aid. In addition, grant aid could reduce borrowing rather than increasing a student's current resources. All these processes serve to equalize the net price across students who received different amounts of TAG aid.

These offsets could make additional TAG aid a net negative under certain circumstances. If the scholarships granted to students in lieu of public aid are persistent over several years while public aid equalizes over time, then the students initially receiving less TAG aid might ultimately receive more financial support and have higher graduation rates. This would manifest as a negative effect of the TAG aid received early in college. The negative effects could also operate through student debt. Marx and Turner, 2018, found that students at community colleges in New York tended to reduce borrowing more than dollar-for-dollar when they received larger Pell Grants, leaving them with less financial resources and hurting their chances of degree completion. Finally, additional aid could lengthen time to degree if it attracts students to stay enrolled at institutions where they are not well-matched (Dillon and Smith, 2020).

Data for Evaluation

Each of the primary steps shown in Figure 2.1 generates administrative records. At the point of filing the FAFSA, a student provides detailed information about the structure of their household and finances, which generates TAG eligibility. A student who accepts their aid package and enrolls in a college will trigger a TAG payment to their college's financial aid office. Following that enrollment, students' persistence and degree completion outcomes will be logged by the college they attend. The Higher Education Student Assistance Authority (HESAA) in New Jersey maintains records of TAG eligibility and payments but had not previously linked these data to information on subsequent college attainment.[3]

[3] The data were stripped of identifying information and shared under the direct control of HESAA for the purposes of generating research evidence to help administer TAG. None of the results in this paper allow for reidentification of any student or family member whose information was included in the data. The data collection and analysis plan were approved by the RAND Human Subjects Protection Committee.

Our data set consists of all TAG recipients during the school years of 2012–2013 through 2018–2019. That period encapsulates some students' entire college career, while for other students it captures just the end, just the beginning, or multiple stints of enrollment. Half of the individuals in the data received TAG in only one year, and half received TAG in multiple years.

Besides TAG eligibility and receipt, we observed a few baseline characteristics of students, including their dependency status from the FAFSA, their class level in college, their age, and, for a subset of students, their federal aid eligibility. We used class level in college and dependency status as control variables in our analysis. Students are considered dependent, and therefore must include their parents' income on the FAFSA, if they are under 24, unmarried, have not served in the military, or do not have children or dependents of their own (Federal Student Aid, undated). Beginning students are either new to college or still consider themselves at the first-year level, based on their self reports on the FAFSA.

We assessed effects of TAG aid in the short term and the longer term. We assessed effects on short-term persistence for students at all levels and at multiple points within an individual's college career. Persistence is accomplished if the student re-enrolls for an additional year of college, potentially by transferring from a community college to a university, or if the student graduates with a degree or credential. We assessed effects on longer-term outcomes by focusing on beginning students and measuring their rates of completion by certain time benchmarks after entering college. For university students, we measured bachelor's degree completion at four, five, and six years. For community college students, we measured completion of any degree or credential and/or transfer to a university at two, three, and four years.

Enrollment and degree completion outcomes for our study were measured via the National Student Clearinghouse (NSC), which covers the vast majority of all college enrollment and degrees in New Jersey and nationwide (National Student Clearinghouse Research Center, 2020). The data are at the level of a school year. Enrollment is indicated by any spell of enrollment during that year (we could not distinguish part-time or partial-year enrollment). Degree completion is indicated by earning any type of degree or credential in that year. The NSC data were drawn in the middle of spring 2020, and they capture nearly all of the New Jersey enrollment that occurred in the 2019–2020 school year (judged by comparing enrollment with prior years). However, the completion records miss most of the degrees in 2019–2020 because earning a degree at the end of spring is common. We therefore tracked enrollment through 2019–2020 and degree attainment through 2018–2019.

One important caveat for this study is that the flagship campus of Rutgers University in New Brunswick, the single largest site of TAG enrollment, is not included in the outcomes data. That campus does not share its NSC data for research by educational institutions such as HESAA. We therefore excluded from the sample all observations where the base year TAG receipt was at that campus, reducing the overall sample of public university TAG recipients by 21 percent. By missing enrollment at this campus, we could understate the rate of transfers from community colleges by a few percentage points.[4]

Table 2.1 describes the characteristics of TAG recipients in the study sample. New Jersey institutions of higher education include 19 community colleges (called county colleges in New Jersey), four public research universities, seven state colleges and universities, 22 independent (private nonprofit) colleges and universities, and a host of proprietary (for-profit) institutions.[5] This study focuses on undergraduates at public institutions and at 14 institutions that are members of the Association of Independent Colleges and Universities of New Jersey (AICUNJ), because our linked data do not consistently cover outcomes at smaller private institutions and the for-profit sector. Together the public universities make up the largest group, with about 30,000 recipients per year. About 26,000 students received TAG each year at the county colleges, and about 10,000 received TAG each year at AICUNJ member institutions.

About one-quarter of public university students were beginning students, compared with 31 percent at AICUNJ member institutions and 59 percent at the county colleges. The younger, dependent group represents 65 percent of TAG recipients at the county colleges, 75 percent at the state colleges and universities, 78 percent at the public research universities, and 83 percent at the independent, private, nonprofit members of AICUNJ.

Table 2.1. Characteristics of Students in Linked Sample

Sector	TAG Recipients over 7 Years	Beginning Students	Dependent Students
County colleges	180,955	59%	65%
State colleges and universities	92,176	25%	75%
Public research universities	115,114	24%	78%
Independent (AICUNJ)	72,064	31%	83%

SOURCE: Authors' calculations using HESAA data. The county colleges sample includes part-time awards.

Prior to this study, the only evidence on outcomes for TAG recipients came from yearly institutional reports of aggregate graduation rates (HESAA, 2020e). Working only from these data, it is not clear what TAG recipients' graduation rates would have been had they received smaller, larger, or no awards. Our empirical strategy uses the data set that HESAA constructed to address these problems, eliminate selection bias, and estimate the effectiveness of TAG.

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[4] About 7 percent of undergraduates at Rutgers–New Brunswick, or about 2,400 students, are transfer students (Integrated Postsecondary Education Data System, 2020). The source of these transfers is not readily available in aggregate data. Assuming that one-third of the 2,400 transfer students at Rutgers–New Brunswick newly arrive from the county colleges each year (a high estimate, considering transfers from other universities and the fact that students could stay more than two years after transferring in) would increase our measure of transfer from 12.4 percent of TAG recipients at county colleges to 15.9 percent.

[5] There are currently 18 county colleges, after Cumberland County College merged with Rowan College at Gloucester County to form Rowan College of South Jersey after the 2018–2019 school year.

3. Cumulative Regression Discontinuity Design

The implementation of TAG imposes several stepwise cutoffs for awards at different income levels. Students on either side of the cutoffs are similar on average but receive TAG awards that differ by hundreds or thousands of dollars. If their outcomes also differ, then we assume that can be attributed to the effects of grant support from TAG. This section describes the program design, how it feeds into an empirical model of TAG effects, and the statistical procedure we used to attain estimates of those effects.

TAG Program Design Details

TAG uses information from the student's FAFSA and state record as inputs to a unique formula. Their method adapts the federal needs analysis to account for New Jersey's demographics and policy goals. The state formula produces the NJEI, which measures each student's ability to pay. The NJEI for TAG recipients can take values from zero to 10,499, with higher amounts signaling a greater ability to pay.

The TAG program divides applicants into ten ranges based on the NJEI. The lowest NJEI range, from 0 to 1,499, triggers the maximum award. The next nine ranges each span 1,000 values from 1,500 to 2,499, 2,500 to 3,499, and so on, and they each correspond to lower and lower award amounts. These ranges are not dollar amounts, nor are they selected to align with any other policy or meaningful distinction between students. The federal methodology for financial aid uses a different index called the Expected Family Contribution (EFC), which does not align with NJEI.[6]

Within each range, there are higher award amounts at higher-tuition sectors and institutions (HESAA, 2020a). Figure 3.1 plots TAG eligibility for the 2018–2019 school year against the NJEI.[7] The levels in the figure represent simple averages (i.e., not student-weighted) across several institutions in three groups: the county colleges, public universities, and AICUNJ member institutions.[8] Clearly, there are some students with slightly different NJEI values (e.g., 1,499 and 1,500) who receive sharply different awards.

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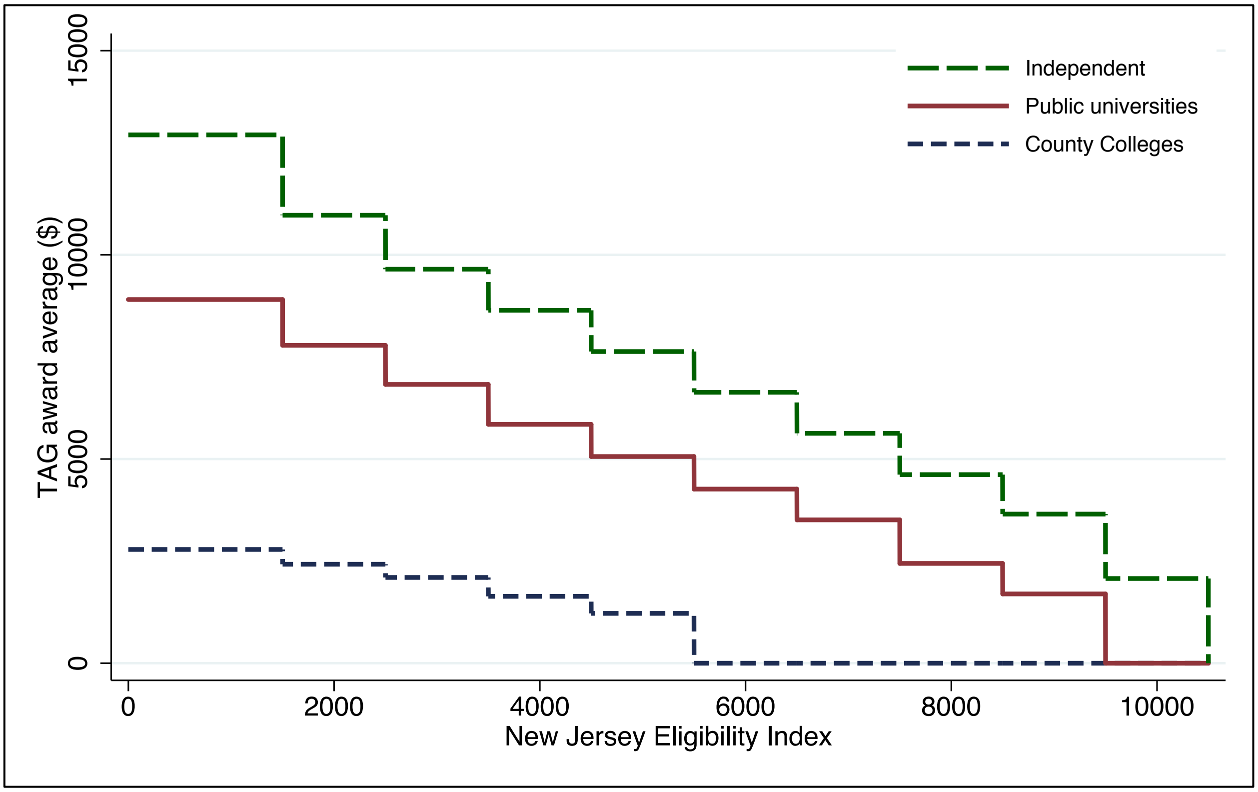
[6] In a subset of our data, school years 2017–2018 and 2018–2019, we observed both the EFC and NJEI. The EFC and NJEI are highly positively correlated in the aggregate, but students at any given NJEI will have a range of EFC values. There are no discontinuous jumps in Pell Grant awards near the NJEI cutoffs.

[7] The TAG award averages are slightly lower in the earlier years of our study. New Jersey tends to increase the TAG amounts by 1 to 2 percent across the board every few years, depending on available funding in the annual state budget process (HESAA, 2020a).

[8] The levels represent the eligibility for TAG for a student who enrolled for the full year. Students must enroll full time to receive TAG, except at the county colleges, where part-time students may receive a prorated award.

Figure 3.1. Relationship Between NJEI and TAG Awards in School Year 2018–2019



SOURCE: HESAA, 2020a. The values represent a simple average across all institutions in these groups. “TAG award” corresponds to eligibility for a full year for a full-time student.

The magnitude of TAG aid is significant relative to the costs faced by enrolled students, but the award’s coverage varies across institutions. Table 3.1 describes the costs and the primary sources of public grant aid in New Jersey, using the most recent year of 2018–2019 as an example. Tuition and required fees represent only part of the official cost of attending college, which also includes an allowance for books and supplies, room and board, transportation, health care, and other expenses.

A maximum TAG award of $2,732 covers 21 percent of the total cost at county colleges, while a maximum TAG award of $9,107 covers 31 percent of the total cost at public research universities. Coverage at state colleges and universities lies in between at 27 percent. The maximum TAG award is largest at AICUNJ institutions, but the mean tuition is also highest there, resulting in TAG coverage of 24 percent. The Pell Grant amount is constant across all sectors at $5,920, but other sources of aid likely differ across sectors. Some institutional discounts and scholarships could directly address the financial need that is unmet by Pell or TAG. These sources of aid are less likely to be available at public institutions (National Center for Education Statistics, undated).

Table 3.1. 2018–2019 Charges and Aid

Sector	Average Tuition and Fees ($)	Average Cost of Attendance ($)	Maximum Pell Grant ($)	Maximum TAG Award ($)	Maximum TAG Coverage of Average Cost (%)
County colleges	4,828	13,018	5,920	2,732	21
State colleges and universities	13,687	27,027	5,920	7,236	27
Public research universities	14,671	29,490	5,920	9,107	31
Independent colleges (AICUNJ)	38,813	53,262	5,920	12,938	24

SOURCE: Authors' calculations using College Scorecard and HESAA, 2020a. Cost of attendance is tuition and fees plus estimated costs for books and supplies, room and board, transportation, health care, and other expenses.

Nearly half of TAG recipients get the maximum awards shown in Table 3.1, but others with higher NJEI values, representing higher incomes, receive smaller awards. Which levels of TAG aid are most effective at meeting students' needs is an important policy question. It is possible that the scaling up of TAG (and the Pell Grant) as income falls does not match the rate at which need increases. On one hand, need might increase faster than public aid as income falls. Then the lowest-income students are still the worst off even after existing aid is applied, and the marginal dollar of grant aid would be the most impactful for them. On the other hand, the lowest-income students' costs might be relatively well-covered by grant aid. Then the need is greater among TAG recipients with higher NJEI values and lower grants but who still have very low incomes. Our analysis tests which of these hypotheses is most consistent with the data by estimating the effects of marginal changes in TAG aid at several income levels and comparing the results.

The same comparisons could be made across sectors, fixing income level. Do increases in TAG aid offset the increased costs at private institutions? Judging only by the percentage of costs covered, TAG appears to have less potential for impact at those institutions than at public institutions under the current structure.

Estimating the Effects of TAG Aid

The TAG program is a classic example of multiple cumulative cutoffs, where all individuals are exposed to the same set of sharp changes in some treatment (TAG awards) at key values of a continuous assignment variable (NJEI). We describe the model that we estimated in more detail in the technical appendix at the end of this report, and we summarize the key points in this section. Most importantly, the logic of a single-cutoff regression discontinuity design extends to multiple cumulative discontinuity design. The multiple cutoff design adds generalizability with only slightly more complexity.

Near each NJEI cutoff, several factors could differ. TAG recipients have observed characteristics (year in college, dependency status) that predate receipt of aid, and they have observed outcomes (college persistence and completion) that follow their receipt of TAG aid. They also have unobserved characteristics (motivation, aptitude) and unobserved potential outcomes (persistence and completion they would have attained if they would have received a different amount of TAG aid).

We assumed that all characteristics and potential outcomes were balanced, on average, among students with very similar NJEI values near the cutoff value. If this assumption holds, then any differences that arise among students immediately on opposite sides of the NJEI cutoff must be attributable to the TAG program. Those treatment effects of landing on the lower side of the NJEI cutoff include receiving additional aid, persisting in college, and eventually completing degrees.

Our identifying assumption is likely to hold because of the way the TAG program is structured. Because the NJEI formula is kept confidential, students have no way of reacting to the cutoffs and adjusting their income or other characteristics to land just below a cutoff and qualify for more aid. Thus, the applicants just above and just below each cutoff are not likely to differ systematically in their motivation or knowledge of the aid program.

We provided support for balance across cutoffs by testing for bunching (potential evidence of students or families actively choosing advantageous NJEI values) and testing for differences in baseline characteristics (potential evidence of underlying differences not attributable to TAG). We also controlled flexibly for observable characteristics in our estimates. Because NJEI is unique to TAG and is only used for TAG eligibility, there are no other program changes occurring at the same NJEI cutoffs. In a subset of our data, we observed eligibility for federal aid and tested for balance in federal aid across the NJEI cutoffs. The results of these tests are discussed in detail in the technical appendix; we found no evidence of students or families manipulating their NJEI to receive larger amounts of aid and no evidence of systematic differences in observable characteristics.

In this model, the effects are identified for students exactly at the cutoffs. In estimation, we used nearby NJEI values to model a local linear regression on either side, and we used the difference in the two fitted lines at the cutoff as an estimator of the regression discontinuity effect. To estimate the effects, we implemented software from Cattaneo, Titiunik, and Vazquez-Bare, 2020. We selected a robust, data-driven bandwidth around each cutoff (Calonico, Cattaneo, and Titiunik, 2014; Calonico et al., 2017). For the local linear regression, we used a triangular kernel, and we appropriately accounted for potential correlation in errors.

All of our outcomes are binary indicators of achieving a certain outcome (persistence or completion). We estimated the percentage point change in the rate of achieving the outcome, and we scaled that effect per $1,000 of TAG aid received during the time period corresponding to the outcome. For the short-term outcomes, we report the increase in the rate of persistence per $1,000 of TAG received in one year—the same year in which eligibility is measured via the NJEI. For the longer-term outcomes, such as four-year completion, we report the increase in the rate of completion per $1,000 of TAG received during a four-year period including the initial year of eligibility and three subsequent years. In this way we leveraged the exogenous variation around NJEI cutoffs to measure the cost-effectiveness of TAG over time periods of varying length.

To implement this scaling, we estimated a two-stage instrumental variables procedure, using the fuzzy regression discontinuity option in the software from Cattaneo, Titiunik, and Vazquez-Bare, 2020. TAG recipients with the same NJEI value receive varying amounts of aid in the short term depending on the school year and institution. They receive varying amounts in the longer term depending on how long they stay enrolled and eligible for TAG. Most importantly, we demonstrated that there is a large and statistically significant "first stage" effect of NJEI cutoffs on aid received. In the second stage, we used fitted values from the first stage model to estimate the effect of TAG dollars on outcomes.

Our study improves on a typical drawback of regression discontinuity designs, which is that they necessarily focus on a local group of individuals with exactly one value of the assignment variable. If the effectiveness of the treatment varies with the assignment variable, then the treatment effect estimated for that group might not be representative of the average treatment effect across the population of interest. Our assignment variable, the NJEI, primarily captures family income, but also assets, household structure, and other variables. We estimated effects at several NJEI cutoffs and averaged together the estimates based on how many TAG recipients appeared near each cutoff. As shown in Figure 3.1, the levels of the cutoffs span the NJEI distribution, with no TAG recipient more than 1,500 NJEI units away from a cutoff.[9] Multiple cutoffs also allowed us to disaggregate the weighted average to answer policy questions about where aid has the greatest effect across income levels.

There are three main complications to this analysis, each stemming from real-world data limitations, that affected our estimates to varying degrees. First, because the data consist of TAG recipients only, the danger of bunching around NJEI cutoffs is greater. Even if students cannot change their NJEI values in response to TAG eligibility, they might be more likely to take up TAG awards—and appear in our data set—when their TAG eligibility is sharply higher on the lower side of NJEI cutoffs. However, we show below that no bunching was detected. The lack of bunching implies that, as discussed above, TAG mainly has effects on persistence and completion, not on initial enrollment and entry into our data set. If there was any bunching from this mechanism, it would tend to bias estimates down: Marginal enrollees induced to enroll by aid might be less likely to persist and complete, and they would be included in the averages for the "treatment" group with more TAG aid.[10]

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[9] Because the NJEI formula is not made public and its components are more complicated than merely measuring income, we cannot describe exactly the levels of financial resources represented at each cutoff and at the extremes.

[10] This is a common issue when using administrative records from postsecondary education. In prior work on the Pell Grant, there was no evidence of enrollment effects that caused students who were eligible for more aid to differentially appear in the database (Denning, Marx, and Turner, 2019).

Second, when implementing a multiple cutoff design, the bandwidth around each cutoff must be small enough that no individual with an assignment value between two cutoffs serves as an untreated observation for one cutoff estimate and a treated observation for another cutoff estimate. Tight bandwidths are a general concern for regression discontinuity because observations with substantially different eligibility values should not be used to represent the individuals exactly at the cutoffs, but in a multiple cutoff design there is the added concern that the cutoffs have enough observations "near" them that each observation can be used to identify the effects for at most one cutoff. The density in our samples was always high enough that the typical bandwidth was around 150 NJEI values. Because the cutoffs were 1,000 units apart, no individual TAG recipient was included in the bandwidth for more than one cutoff. Estimating with alternative bandwidths that were slightly larger or smaller did not yield significantly different results.

Third, in our data set, there are unobserved mediators. We cannot tell how much a student received in institutional grants, scholarships, or discounts. We also cannot tell how much they borrowed. This does not introduce bias in the estimate of the effect of TAG aid, but it does change the interpretation of our results. If last-dollar aid from other sources reacts to TAG eligibility, then TAG's effect on financial resources is smaller than we measure. In that case, the reduced-form effect on educational outcomes that we estimated could be understating the effect that TAG dollars could achieve if other aid programs were held constant. Furthermore, if last-dollar aid from other sources reacts to initial TAG eligibility and then remains part of a student's aid package in subsequent years, then the initial sharp increase in TAG aid could actually have caused a net loss in financial support over time, potentially leading to a negative effect of being below an NJEI cutoff.

4. TAG Effects by Context

There are 1,920 mini-experiments that naturally occur at each stepwise jump in TAG eligibility over 52 colleges in 7 years. We implemented our empirical strategy by combining groups of these cutoffs to maximize the sample size and homogeneity of student groups. Although sample size and homogeneity both serve to increase the precision of effect estimates, they work against one another in our finite sample: Adding more students to the estimation at some point causes us to begin to add dissimilar students.

As discussed above, we were guided in this process by short-term and longer-term outcomes, income levels, and college sectors. In all cases, we grouped together cohorts of TAG recipients across school years. In testing (not reported here), we did not discover heterogeneity in effects from school years early in our sample window (beginning school year 2012–2013) to later in the sample window (ending school year 2018–2019). In all cases, we scaled the effects of TAG aid across individuals by the percentage point change per $1,000 of aid caused by the jump in eligibility at the NJEI cutoff. The same conclusions were evident when we scaled aid by the percentage of tuition covered or the percentage of costs covered. Using this dollar metric, we compared our estimates with relevant estimates of the cost-effectiveness of other need-based aid programs from the literature.

Finally, for each sample we report a weighted average across multiple cutoffs as well as our estimate for the lowest cutoff. We report the results of statistical tests of the difference between the effect at that lowest cutoff and the weighted average effect at all of the higher ones. In this way we assessed whether the effects of TAG differed for the lowest-income recipients who represent the largest group served by the program.

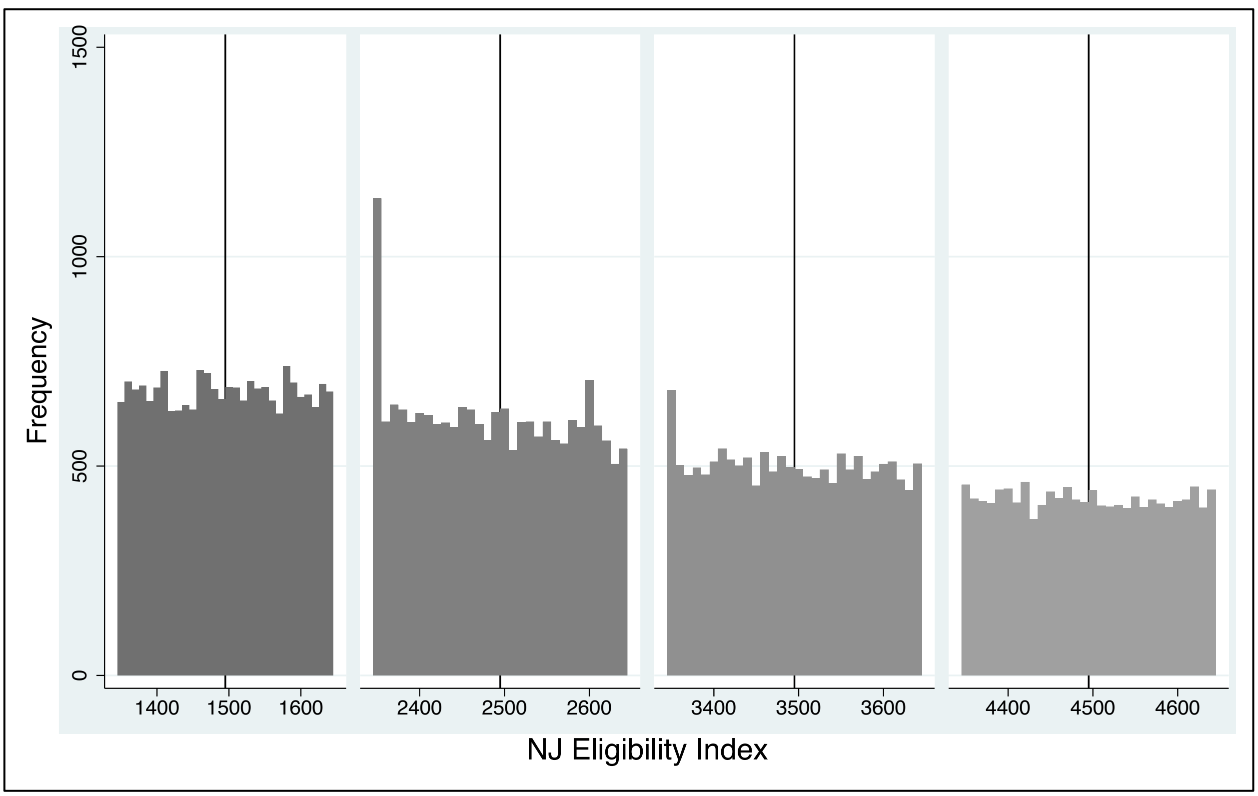
All the estimates appear in Table 4.1. Table A.1 in the technical appendix reports sample sizes and the tests for bunching for all estimates in Table 4.1. For two selected samples, we also show three key graphical representations of the results of our analysis: the density of TAG recipients near cutoffs (to test for bunching), the first-stage effect on TAG aid received, and the reduced-form effect on persistence or completion outcomes.

Short-Term Outcomes for All TAG Recipients

We estimated short-term effects on persistence using the broadest possible sample of TAG recipients. The only sample restriction is that we only considered students local to the first four cutoffs that are shared by all sectors and years, at NJEI values of 1,500, 2,500, 3,500, and 4,500. The higher cutoffs are only relevant for universities, with the highest few only relevant for AICUNJ institutions. If we included those cutoffs, then we would add middle-income students only from universities, confounding variation in income with college sector. In the longer-term, sector-specific analyses, we used all available cutoffs. The estimation procedure selects a bandwidth for each cutoff, and the resulting selections range from 100 to 200 NJEI values. However, all the figures in this section display a bandwidth of 150 values around each NJEI cutoff.

Figure 4.1 shows the density of applications to test for bunching below NJEI cutoffs where aid is more generous. Visual inspection does not indicate any bunching. Estimation of the imbalance using the method proposed by Cattaneo, Jansson, and Ma, 2020, yields no evidence of bunching either. In fact, the point estimate suggests higher densities on the right-hand side, where grants are smaller, but the difference is not statistically significant (*p*-value 0.59). To provide further support that there are no sharp differences among students across cutoffs, we estimated the placebo effect of TAG aid on baseline characteristics of dependency status, age, and the federal EFC. These tests (not shown) indicated no imbalance across the cutoffs: The estimated differences were small and not statistically significant.

Figure 4.1. Frequency of NJEI Values Near Cutoffs, All TAG Recipients

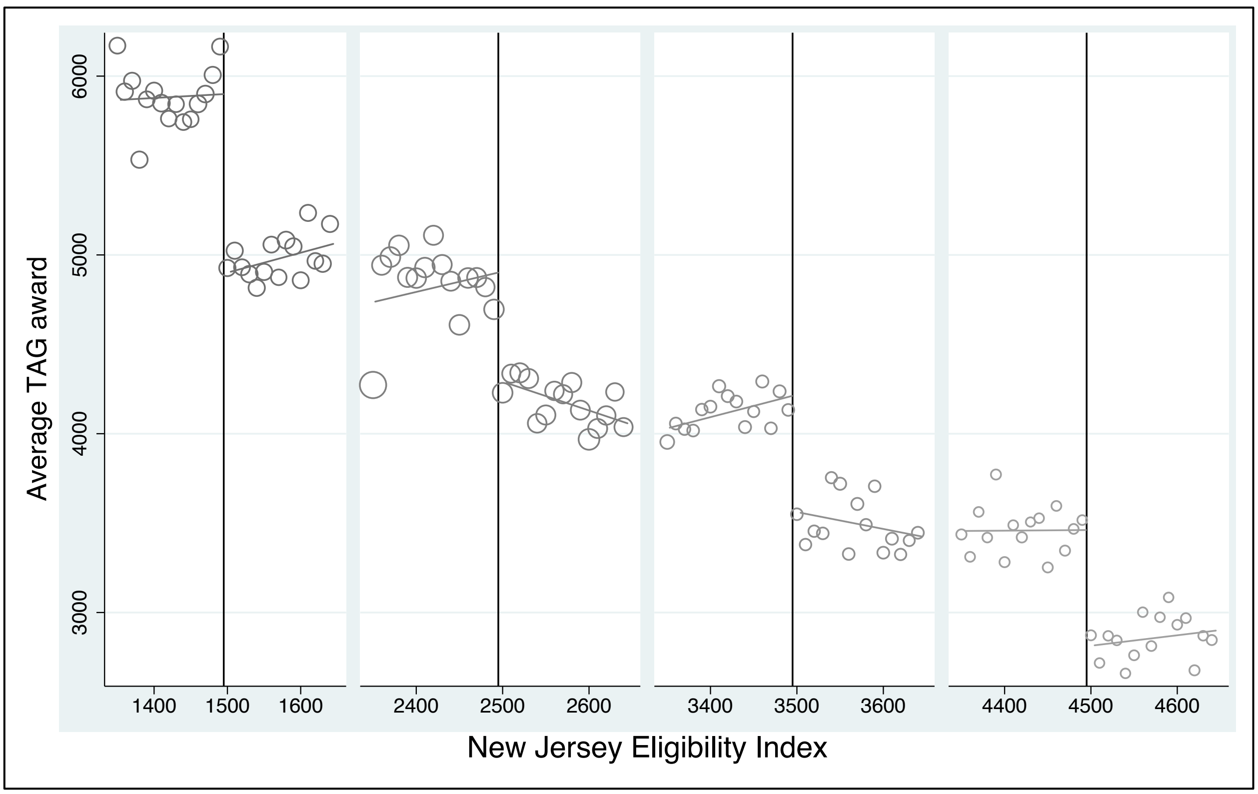


SOURCE: Authors' calculations using HESAA-NSC data. Bars represent bins of 10 NJEI values, and frequencies represent TAG recipients across all college sectors with NJEI values in these ranges during 2012–2013 through 2018–2019.

Figure 4.2 shows the empirical version of the formulaic TAG schedule displayed in Figure 3.1. It is a scatter plot where each bubble represents the average TAG dollars received by students in a range of ten NJEI values. The sizes of the bubbles are proportional to the frequency of observations in those bins (corresponding to the frequencies shown in Figure 4.1). The variation across bins comes from combining several different institutions and years in different mixtures within each bin. Producing this graph for one institution and year would yield a sharp stairstep function.

On either side of each cutoff, the plotted lines represent the estimated local linear regressions. The difference between the lines at the cutoff is the reduced-form, unadjusted estimate of the difference in aid at the cutoff. Our estimation procedure adjusts the comparison for covariates (dependency status, year in college, school year, and college sector) and averages together the effects at each cutoff, weighted by the number of observations near each cutoff (within a cutoff-specific bandwidth selected as part of the estimation). The resulting estimated difference in TAG aid across the cutoffs is $646 in this sample.

Figure 4.2. First-Stage Effect on Short-Term TAG Award, All TAG Recipients



SOURCE: Authors' calculations using HESAA-NSC data. Dot sizes correspond to the frequencies from Figure 4.1.

Figure 4.3 is structured the same as Figure 4.2, but it reports the rate of persistence on the vertical axis. Students persist if they earned a degree or credential in the year they received TAG aid and/or they enrolled in any college or university in the year following receipt of TAG aid.

Visually inspecting the figure, each of the cutoffs shows more persistence on the left-hand side, where grants are larger.

Figure 4.3. Reduced-Form Effect on Short-Term Persistence, All TAG Recipients

SOURCE: Authors' calculations using HESAA-NSC data. Dot sizes correspond to the frequencies from Figure 4.1. *Persistence* is defined as a binary variable capturing any enrollment in any college or university in the year following the base year with receipt of TAG aid based on these NJEI values.

Table 4.1 provides the adjusted, weighted-average estimate of TAG effects on short-term outcomes. The effect on persistence in the broadest possible sample, including all sectors, is an increase of 1.4 percentage points, though the estimate is not statistically different from zero. The sample average is an 82.2-percent rate of persistence. In a review of dozens of studies of need-based aid, Nguyen, Kramer, and Evans, 2019, found increases of 1 to 2 percentage points in persistence and completion per $1,000 in aid.

Table 4.1 reports results from the same analysis with samples restricted by sector. Table A.1 shows no evidence of bunching for any of the sector-specific samples. At the county colleges, the sample average rate of persistence was lower, at 73.6 percent, but the estimated effect was larger, at 4.9 percentage points. Again, this estimate was not precise and was not statistically distinguishable from no effect. At both public and private universities, the sample average rate of persistence was higher, at over 88 percent, and neither had large or significant point estimates for persistence.

Table 4.1. Effects of an Additional $1,000 of TAG Aid

Outcome Time Frame and Sample	Sample Average	Effect Estimate (*p*-value): All Income Levels	Effect Estimate (*p*-value): Lowest Income Cutoff
Short-term **persistence, all students** Percentage who graduate or re-enroll within 1 year of receipt (4 shared cutoffs, controls for grade, year, dependency status)			
All students (controls for sector)	82.21	1.38 (0.30)	1.31 (0.49)
County colleges students	73.58	4.85 (0.39)	9.00 (0.35)
Public university students	88.84	0.53 (0.70)	–0.71 (0.63)
AICUNJ students	88.18	1.09 (0.43)	0.12 (0.79)
Longer-term completion, beginning at **county colleges** Percentage who earn **credential or transfer to university** (4 shared cutoffs, controls for year, research institutions, dependency status)			
2-year completion	11.94	0.05 (0.98)	5.01 (0.22)
3-year completion	24.40	–1.11 (0.46)	2.49 (0.63)
4-year completion	31.60	1.12 (0.41)	5.45 (0.05)*
Longer-term completion, beginning at **public universities** Percentage who graduate with **bachelor's degree** (6 shared cutoffs, controls for year, dependency status)			
4-year completion	34.63	2.67 (0.03)**	1.02 (0.33)
5-year completion	53.67	1.57 (0.20)	0.51 (0.61)
6-year completion	60.09	0.67 (0.62)	–0.09 (0.92)
Longer-term completion, beginning at **AICUNJ institutions** Percentage who graduate with **bachelor's degree** (9 shared cutoffs, controls for year, dependency status)			
4-year completion	42.05	–2.43 (0.01)**	2.11†† (0.14)
5-year completion	56.66	–1.13 (0.12)	1.88† (0.13)
6-year completion	61.39	–0.33 (0.64)	1.68 (0.19)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ for test of effect equal to zero.
† $p < 0.10$, †† $p < 0.05$, ††† $p < 0.01$ for test of equality in estimates between lowest income cutoff and higher cutoffs.
SOURCES: Authors' calculations using HESAA-NSC data and multiple cumulative regression discontinuity design software from Cattaneo, Titiunik, and Vazquez-Bare, 2020. Where students can appear multiple times (e.g., short-term persistence containing all TAG recipients), the standard errors are robust to clustering within an individual. We used local linear estimation with a triangular kernel and nearest-neighbor matching, with robust, data-driven bandwidth selection. Effect estimates are given in percentage points per $1,000 of TAG aid received during the relevant period—e.g., aid received over four years for four-year degree completion outcomes.

Examining effects at the lowest-income cutoff did not yield significantly different effects for persistence. The estimate for county colleges was a 9-percentage-point increase, but it was not statistically significant in a relatively small sample (see Table A.1).

Overall, there was suggestive evidence that TAG increases persistence, particularly for community college students. Because rates of persistence are so high among enrolled university students (and students in general), we looked for effects of aid on less commonly achieved, longer-term outcomes, such as degree completion and transfer.

Longer-Term Completion Outcomes

In this subsection, we estimate longer-term effects. The sample is restricted to students enrolling in college for the first time in the county colleges, public universities, and AICUNJ member institutions, respectively. The outcome of interest is college completion by yearly benchmarks. In each sector, the analysis includes all the relevant cutoffs in effect for each year, as noted in Table 4.1. The first-stage effect on TAG aid, by which the effect estimates are scaled, is measured over the same time period as the outcome. For example, the percentage point change in four-year bachelor's degree completion is scaled in terms of thousands of dollars of TAG aid received over four school years.

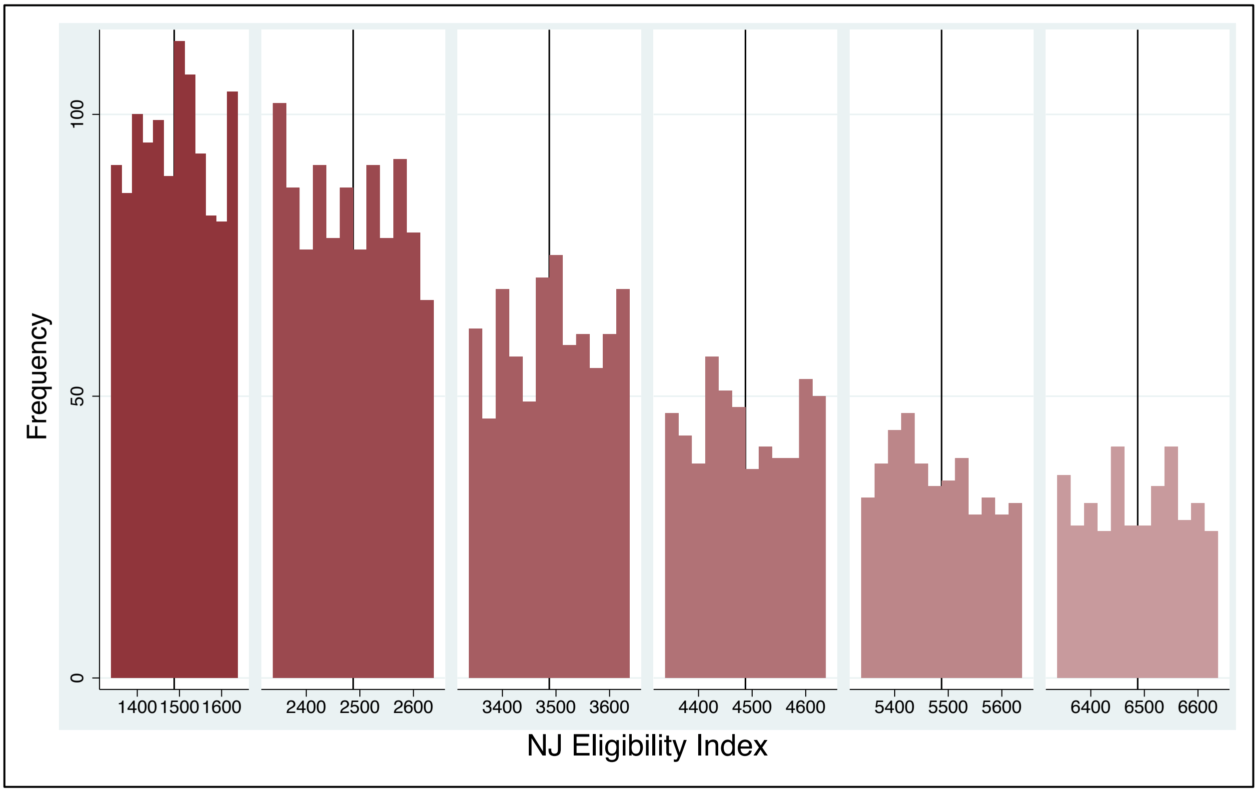
At the county colleges, our completion measure includes earning any degree or credential or transferring to a university. We assessed effects at two-, three-, and four-year benchmarks. The sample average rate of completion was about 12 percent after two years, 24 percent after three years, and 32 percent after four years. Students move in and out of community college much more commonly than they do at universities, and these are typical completion rates over such short spans of time after initially entering school (Goldrick-Rab, 2010).

Prior work shows evidence that state-funded financial aid can increase completion of community college degrees and credentials over a three-year time frame (Anderson, 2020b). In that study, the lowest-income recipients of Wisconsin's need-based grant saw significantly higher benefits per dollar of aid than middle-income recipients, showing that they experienced more need even after receiving maximum Pell Grants. Gurantz, 2020, estimated a precise zero effect of state aid to California community college students, focusing on a wider range of incomes.

We found little evidence of positive effects averaging over all cutoffs for community college students, but there were large positive point estimates for the lowest-income TAG recipients. For two-, three-, and four-year completion, we estimated increases of 5.0, 2.5, and 5.5 percentage points, respectively, with the last marginally statistically significant. The magnitudes of these effects, per $1,000 in aid, are similar to those in Anderson, 2020b. There was no evidence of bunching or imbalance in any of these samples (see Table A.1). However, the estimates for the lowest-income groups were not statistically different from the estimates in moderate-income groups.

Moving on to university students, we highlight the case of on-time bachelor's degree completion at public universities and plot the figures behind the numerical estimates. Figure 4.4 shows the density of applications to test for bunching below the first six NJEI cutoffs. Visual inspection and formal testing again suggest somewhat higher density on the higher side of the cutoffs, providing no evidence that students manipulated their NJEI to receive more aid (*p*-value of density test 0.44). The estimated difference in the percentage who are dependent (a test of balance across the cutoffs) was small and not statistically significant.

Figure 4.4. Frequency of NJEI Values Near Cutoffs, TAG Recipients at Public Universities

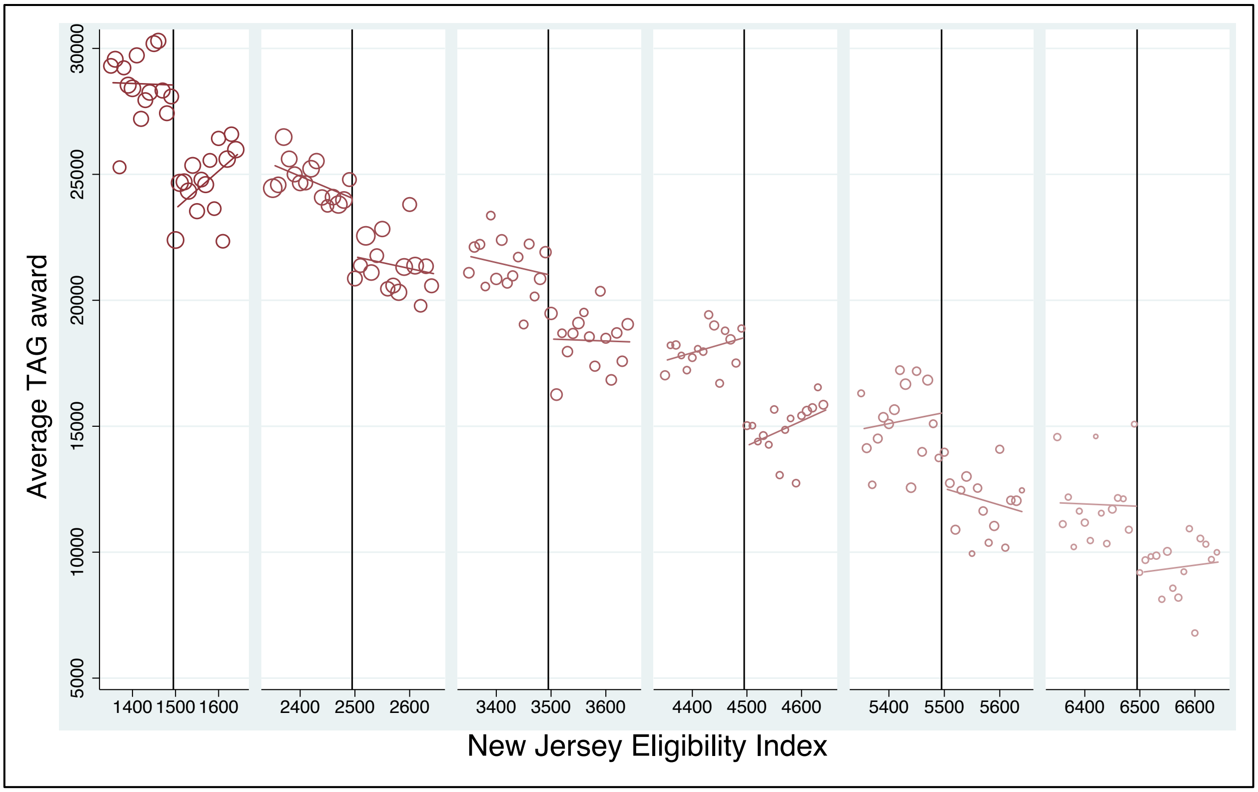


SOURCE: Authors' calculations using HESAA-NSC data. Bars represent bins of 25 NJEI values, and frequencies represent TAG recipients at public universities with NJEI values in these ranges during 2012–2013 through 2015–2016.

Figure 4.5 shows the amount of TAG received over four years. Students on the lower side of the cutoffs when they started college received, on average, an additional \$825 in TAG aid in the base year and an additional \$3,299 cumulatively over four years.

Figure 4.6 shows the four-year graduation rate at public universities. At several of the cutoffs, most notably the first two, the rate of graduation is higher on the lower side of the cutoff, indicating positive effects of additional TAG aid.

Figure 4.5. First-Stage Effect on TAG Award Received over Four Years, TAG Recipients at Public Universities



SOURCE: Authors' calculations using HESAA-NSC data. Dot sizes correspond to frequencies in bins of 10 NJEI values.

The regression estimates indicate that an additional $1,000 in TAG grants over a four-year period increased on-time degree attainment by a statistically significant 2.6 percentage points. The sample average graduation rate was 34.6 percent. Table 4.1 additionally reports effects at five-year and six-year benchmarks, where the sample average rates of completion were 53.6 percent and 60.1 percent, respectively. The smaller estimated effects on five- and six-year graduation suggest that students who received less TAG aid caught up over time, equalizing the graduation rate by six years. Still, an increase in four-year graduation indicates that TAG grants supported faster completion of degrees, as well as potentially supporting some degrees that would not be attained otherwise. Estimates were statistically indistinguishable for lower- and moderate-income groups in this sector.

This analysis is comparable to the regression discontinuity analysis of the Pell Grant for public university students in Texas by Denning, Marx, and Turner, 2019, who found that an additional $1,000 in Pell Grant aid increased five-year graduation rates by 5 percentage points, from a baseline graduation rate of 31 percent. Their analysis focused on students near one eligibility cutoff of around $30,000 in annual household income. Using a similar approach, Castleman and Long, 2016, found an increase of 6 percentage points in the six-year graduation rate of students in Florida, corresponding to an additional $1,000 in state aid across all types of institutions.

Figure 4.6. Reduced-Form Effect on Four-Year Bachelor's Degree Completion, TAG Recipients at Public Universities

SOURCE: Authors' calculations using HESAA-NSC data. Dot sizes correspond to frequencies in bins of 10 NJEI values. *Graduation* is defined as a binary variable capturing a degree earned at any university within four years following the base year with receipt of TAG aid based on these NJEI values.

Estimating the same set of analyses for students beginning at the private, nonprofit members of AICUNJ yielded less conclusive, and at times negative, results. There was no evidence of imbalance or bunching across any of the nine cutoffs that apply to private college students (see Table A.1). As discussed above, TAG awards in this sector are larger in dollar terms but smaller in terms of tuition coverage. Increases in resources are made even smaller wherever institutional aid offsets TAG aid, which is a common phenomenon that is not measurable in our data (Turner, 2019). AICUNJ is the smallest TAG sector in this study by total recipients. The sample average rates of degree attainment were somewhat higher than at public universities: 42.1 percent, 56.7 percent, and 61.4 percent at the four-, five-, and six-year benchmarks, with wide variation across starting institutions.

The point estimate for four-year completion was significantly negative, a puzzling result. This implies that students who initially received less TAG aid ended up with higher rates of degree completion. As discussed above, if other grants and scholarships filled in the gap and then persisted over subsequent years, that might induce a net loss over time from initially receiving more state aid. The negative effect fades over five- and six-year time periods, suggesting that the two groups equalized over time.

Like the county colleges analyses, wherever there were null or negative point estimates for the multiple-cutoff average, there were always large and positive point estimates for the lowest-income cutoff. Effect estimates of 2.1, 1.9, and 1.7 percentage points for the lowest-income students were all nearly statistically significant even in relatively small samples. In the case of four-year completion at the AICUNJ institutions, the effect estimate for the lowest income level was statistically significantly higher than the effect estimate for moderate income levels. This is suggestive evidence that TAG works best for the lowest-income students at the private colleges, where it provides the largest grants and the largest marginal jump in aid.

5. Informing Financial Aid Policy

Summary of Results

This study is the first to rigorously evaluate TAG, an important program in New Jersey and a prime example of need-based financial aid, a type of program that exists in nearly all states and at the federal level. TAG increased on-time bachelor's degree completion at public universities, the sector where TAG has the most recipients and covers the largest percentage of tuition costs. Per $1,000 of aid over four years, the grant increased graduation rates by 2.6 percentage points. In other sectors where TAG serves fewer students and covers a smaller percentage of tuition, the evidence for cost-effectiveness was less clear.

This study is an innovative addition to a growing literature using natural experiments to evaluate the effects of financial aid for college students. Our study disaggregated several income levels rather than focusing on one cutoff or an opaque mix of income levels. We were able to undertake multiple studies within one framework by applying the same statistical estimation approach across several student groups facing different college attainment decisions. Throughout the analysis, we held constant the location and time period, the overall economic environment, and the program application rules. Any one of these factors can account for differences in effects of financial aid, and they are usually confounded with each other when aggregating research evidence across studies. A randomized experimental set of studies on a smaller, privately funded aid program in Wisconsin had a similar ability to hold factors constant and found similar results: Aid increased on-time bachelor's degree completion but had muted effects for longer-term outcomes and community college students (Anderson et al., 2019).

Following Anderson, 2020b, this study is the first to estimate how effects of college aid vary by income in a large public program, and the first to focus on university students. For public leaders allocating scarce resources based on student needs, it is important to know which students benefit most from additional grant aid. If increments in aid cause larger increases in college attainment at lower income levels, that suggests increasing grants for those students or protecting their grants in the case of funding cuts. That was most clearly the case for AICUNJ students, where the lowest-income group benefited from TAG aid while moderate-income groups getting more TAG aid actually had lower rates of on-time graduation. The positive effects were similar across income levels at public universities.

Limitations

This study faces some of the same limitations as prior research, and not all the conclusions are clear-cut. We lack data on the complete financial picture of aid applicants. Knowing more about their sources of income and financial aid would help us understand the mechanisms for

TAG aid to help support persistence and graduation. For example, we could describe whether students who receive additional financial aid choose to work less. This type of analysis is feasible if college records are linked with earnings and employment records from state unemployment insurance systems. Our data have other limitations, such as the relatively short time frame for most of the cohorts involved and the lack of outcome data for the single largest campus in the state, Rutgers University in New Brunswick.

The methods in this study recover estimates of effects for students with NJEI values near the cutoffs (1,500, 2,500, etc.). It is unlikely that the groups with intervening values of NJEI (2,000, 3,000, etc.) have significantly different responsiveness to aid than their neighbors. However, it is possible that students with very low NJEI values (below 1,250 or so) might have different needs. Our estimates might not extrapolate to this population, who have the very lowest incomes, or to what would happen if the program were expanded above and beyond its current income range.

Assessing how aid interacts with other kinds of supports is an important area of analysis, one that is outside the scope of our study using large-scale administrative data. There is growing evidence that students, particularly at community colleges, benefit from being connected to transportation, academic counseling, and other benefits (Sommo and Ratledge, 2016; Evans et al., 2020; Daugherty, Johnston, and Berglund, 2020).

Because the vast majority of TAG costs are captured in the grants themselves, our estimates accurately represent the cost-effectiveness of the program. A more complete cost-benefit analysis of TAG for the state would require monetizing the benefits, such as increased productivity and tax revenues. The results of that analysis would allow for a more direct comparison of the net benefits of aid programs relative to the net benefits of wraparound supports for students.

Finally, we were not able to explore differences in effectiveness of TAG by student characteristics such as first-generation status, gender, or race and ethnicity because we lacked data on these measures. Prior research has shown important differences by student characteristics (Page and Scott-Clayton, 2016). Ultimately, the state policy is likely to be applied equally to all students regardless of these types of demographics, but uncovering variation in the effects of aid could signal areas of focus for other support services.

Evidence for Policy Action

TAG and other similar programs have existed for decades, but gaps in college attainment by income have widened significantly during the 2010s (Cohn, 2020). During this same time period, federal aid and many state aid programs failed to keep pace with tuition and enrollment growth (Baum et al., 2019).

New Jersey is one of the few places where financial aid has remained consistently strong. TAG is the most generous need-based financial aid program, considering total funding per state resident undergraduate (National Association of State Student Grant & Aid Programs, 2018). Out of all full-time undergraduate students in the state, over a third receive a TAG award, with an average award of over $6,000 annually (HESAA, 2018). The broad reach of the program and its commitment to funding all eligible students has led to massive growth: TAG spending grew by 86 percent in nominal terms over the decade from 2007–2008 to 2017–2018 (HESAA, 2018). On a per-recipient basis, the grant has increased in value by 64 percent, just keeping pace with the increases in public university tuition during that period (Ma et al., 2019). Funding for TAG was held roughly constant at $440 million for fiscal year 2021 even as New Jersey imposed over $1 billion in cuts and efficiencies in response to the pandemic (Murphy and Oliver, 2020).

Looking to the future, New Jersey is pursuing a goal of college degrees for 65 percent of its adult population by 2025 (State of New Jersey, 2019). One way to generate more bachelor's degrees in four years would be to increase funding for TAG and proportionally increase all awards, as the state has done multiple times recently (HESAA, 2020a). The public university sector receives most of the program funding, and our results show that incremental additions to TAG awards for recipients in that sector increased their rates of on-time bachelor's degree completion. Without additional funding from the state, HESAA and its board could reshape aid eligibility by shifting the TAG schedule so that more funding goes to relatively lower-income students at private nonprofit institutions. Our estimates suggest that funding more of the lowest-income students at the maximum award amount is likely to have a significantly greater positive effect on four-year graduation rates than funding more of the moderate-income students at a lower award amount.

Broader objectives, such as transparency, stable funding, and extending aid to part-time students or for longer careers, are all potential reforms (Anderson, 2020a; Urban Institute, 2020). The results in this study add to the growing base of evidence showing that while these reforms develop, lower-income students can still benefit from public need-based aid.

Technical Appendix

This appendix provides details about our statistical analysis, moving from a general conceptual model toward specifics based on our setting and data. First we describe how a multiple regression discontinuity design can be implemented as a model relating financial aid eligibility to college outcomes. This is a two-stage model where cutoff values in the NJEI cause sharp jumps in TAG aid, and then the aid potentially causes changes in college persistence and graduation. Second, we specify estimating equations in order to make the timing and measurements clear. Third and finally, we provide details about the data samples used in each estimate reported above. Table A.1 reports the sample sizes within the selected bandwidths and the results of tests for bunching on the lower side of NJEI cutoffs where aid eligibility is greater. Overall, the data fit the concept well.

Two-Stage Empirical Model

Cattaneo, Titiunik, and Vazquez-Bare, 2020, define a model of regression discontinuity treatment effects at multiple cumulative cutoffs. As in a standard regression discontinuity design, each treatment effect is identified exactly at a cutoff value. The effect is the difference in two limits taken as the assignment variable approaches the cutoff from above and from below. The input to these limits is the expected value of the outcome, conditional on the value of the assignment variable and potentially other observable covariates.

Unlike a standard design with one cutoff, estimating the multiple-cutoff model yields a weighted average of several effects, with bandwidths and weights estimated corresponding to the density of observations near each of several cutoffs (Cattaneo et al., 2016). This weighted-average approach improves on the standard "pooled" approach to multiple cutoffs, which is to redefine the assignment variable relative to the cutoffs so that all the cutoffs coincide at the same value for all individuals. That restrictive approach leads to a different set of weights and forces all bandwidths to be equal for all cutoffs, potentially introducing bias and imprecision.

In any regression discontinuity with multiple cutoffs and different treatments, the average treatment effect will estimate a mix of effects of treatment levels occurring across the various cutoffs. The effect of "greater eligibility for TAG" is harder to interpret than the effect of $1,000 of TAG aid. We therefore scaled the effect estimates by a first stage that captures the increase in financial aid that is triggered by treatment (an NJEI value below the cutoff). The cost-effectiveness per $1,000 is comparable with other studies (Nguyen, Kramer, and Evans, 2019).

This two-stage approach does impose subtle, implicit assumptions about how effects per dollar vary across baseline levels of aid and increments of aid. First, this approach does not allow for effects to differ based on the starting point. If TAG increases a student's aid from $1,000 to

$2,000, that is treated similarly to TAG increasing a student's aid from $5,000 to $6,000. Second, the estimate is a linear interpolation across dollar values of aid. The implicit assumption is that the effect of $1,000 in TAG aid is half the effect of $2,000 in TAG aid. These implicit assumptions might not hold if, for example, there are diminishing effects of larger total dollar amounts, or if there are negligible effects of particularly small increments. Research has not been able to trace out the way effects vary at different levels of aid and different-sized aid increments. Policy choices have tended to favor grants that are never less than a few hundred dollars but also never cover all college costs. To estimate the full range of potential effects, researchers would need more examples of variation besides the existing increments, or strong assumptions on functional forms.

Estimating Equation

The conceptual model states that educational outcomes are influenced by some function of financial resources and individual characteristics. This section states the function explicitly. As discussed above, this implicitly rules out some of the interactions between starting levels of finances, increments of aid, and individual characteristics. However, the variation created by the TAG eligibility function helps rule out major sources of bias among students local to NJEI cutoff values.

The reduced-form model at each cutoff c in the set of cutoffs C can be expressed as follows.

$$Y_{it} = \rho^c G_{it}^c + f^c(v_{it}) + \varepsilon_{it}, i: v_{it} \in [v^c - a^c, v^c + a^c], c \in C$$

This equation models the outcome Y_{it} for individual i relative to school year t of TAG receipt. For example, the outcome of four-year degree completion is a binary indicator for having completed any degree within four years of year t. The graduation outcome analyses focus on cohorts of entering students who all began college in school year t, so that there is exactly one observation for each individual i. The persistence outcome analyses allow for multiple observations for individuals who filed the FAFSA in multiple school years. In these cases, we implemented cluster-robust nearest neighbor variance estimation to calculate standard errors allowing for correlation within an individual.

The outcome is a function of an indicator G_{it}^c, which equals to one if the NJEI for individual i is below cutoff c in year t. The outcome can also be influenced by the NJEI value v_{it}. In this equation, there is a control function $f^c(v)$ for each cutoff c, and these functions can be arbitrarily flexible but are assumed to be continuous through each critical cutoff value v^c. ε_{it} is an idiosyncratic error term with mean zero.

In estimation, the functions $f^c(v)$ are each modeled using local linear regression and allowed to differ in slope and intercept on either side of the cutoff value v^c. The local linear regression is modeled using observations i within a balanced bandwidth a^c around each cutoff. The software provided by Cattaneo, Titiunik, and Vazquez-Bare, 2020, jointly estimates the parameters of this equation, as well as the bandwidths, standard errors, and weights at all of the cutoffs.

To implement the two-stage estimates of cost-effectiveness, we define aid in the first stage as the total TAG aid in thousands of current dollars, received during the same time frame in which the outcome is measured.

The resulting two-stage model can be expressed as follows.

$$T_{it} = \tau^c G_{it}^c + g^c(v_{it}) + \boldsymbol{X}_{it}'\boldsymbol{\gamma} + \mu_{it},, i: v_{it} \in [v^c - b^c, v^c + b^c], c \in C$$

$$Y_{it} = \pi^c \tilde{T}_{it} + h^c(v_{it}) + \boldsymbol{X}_{it}'\boldsymbol{\beta} + \xi_{it},, i: v_{it} \in [v^c - b^c, v^c + b^c], c \in C$$

For three-year degree completion, TAG aid T_{it} represents thousands of dollars in TAG aid received in years t, $t + 1$, and $t + 2$, cumulatively. For one-year persistence, TAG aid T_{it} represents thousands of dollars in TAG aid received in year t only.

The first stage predicts TAG aid as an outcome, using a similar approach to that described above. The second stage models the effect of fitted values $\tilde{T}_{it}$ from the first stage, using a similar approach again. The bandwidths b^c are the same in the first and second stage. The local control function will vary depending on the outcome, as will the estimated parameters and the error term. A weighted average of the parameters π^c is what we report in Table 4.1, along with the first cutoff value π^1.

The key assumption underlying this two-stage model is that being just below an NJEI cutoff only affects outcomes via its effect on TAG aid. This assumption is likely to hold because the NJEI is not used for any other program.

This pair of equations includes a vector of controls $\boldsymbol{X}_{it}$ which include indicators for the school year t (e.g., 2012–2013), indicators for the sector where the student i received TAG aid in school year t (e.g., research universities), and indicators for each individual's year in college and dependency status on the FAFSA filed in school year t. In all cases, the conclusions are robust to the inclusion or exclusion of controls.

Sample Sizes and Tests for Bunching

Table A.1 reports two key supporting statistics for every estimated effect in Table 4.1. First, it reports the number of TAG recipients (student-year observations) within the chosen bandwidths around each cutoff. Second, it reports the results of testing for bunching across the cutoffs. If the reported t-statistic is positive, that indicates a higher density immediately on the lower side of the NJEI cutoff where TAG aid is greater. If the reported t-statistic is large in absolute value, then the difference in density is statistically significant. Large differences raise concern that other characteristics might not be balanced across the cutoffs and that the estimates could be biased in some way.

As discussed above in Section 4, none of the estimates for multiple cutoffs give cause for concern. Several of the tests for samples of students at public institutions yielded negative t-statistics, suggesting that, by chance, more students enrolled and received TAG on the higher side of NJEI cutoffs where less aid was awarded.

The tests for bunching around only the lowest income cutoff were more variable and sometimes statistically significant. As can be seen in Figure 4.4, there are many more TAG recipients just above the lowest cutoff among public university students in the four-year bachelor's degree completion sample. The difference is statistically significant, and a similar-sized and significant difference appears for the five-year bachelor's degree completion sample. The implications of this imbalance are that more marginal students appear in the "untreated" averages, potentially introducing a downward bias in the estimates of TAG effectiveness for the lowest-income students at public universities.

Table A.1. Sample Sizes and Tests for Bunching

Outcome Time Frame and Sample	Sample Size Within Bandwidth: All Income Levels	Sample Size Within Bandwidth: Lowest Income Cutoff	*t*-Statistic for Estimated Bunching Below Cutoff: All Income Levels	*t*-Statistic for Estimated Bunching Below Cutoff: Lowest Income Cutoff
Short-term **persistence, all students** Percentage graduating or re-enrolling (4 shared cutoffs, controls for grade, year, dependency status)				
All students (controls for sector)	73,114	27,940	–0.54	1.15
County colleges students	27,263	7,895	–1.29	–1.21
Public university students	30,336	5,835	1.01	1.58
AICUNJ students	10,167	4,072	0.86	1.58
Longer-term completion, beginning at **county colleges** Percentage earning a **credential or transfer to university** (4 shared cutoffs, controls for year, research institutions, dependency status)				
2-year completion	15,654	5,584	–1.14	–1.16
3-year completion	13,890	3,471	–1.41	–1.26
4-year completion	10,963	3,664	–0.82	–0.64
Longer-term completion, beginning at **public universities** Percentage graduating with **bachelor's degree** (6 shared cutoffs, controls for year, dependency status)				
4-year completion	4,001	1,086	–0.77	–2.15**
5-year completion	3,146	734	0.16	–2.01**
6-year completion	2,155	618	0.32	–1.81
Longer-term completion, beginning at **AICUNJ institutions** Percentage graduating with **bachelor's degree** (9 shared cutoffs, controls for year, dependency status)				
4-year completion	2,224	452	0.26	–0.25
5-year completion	1,662	347	0.16	–0.52
6-year completion	1,042	316	1.18	0.68

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
SOURCES: Authors' calculations using HESAA-NSC data and multiple cumulative regression discontinuity design software from Cattaneo, Titiunik, and Vazquez-Bare, 2020, and the density test from Cattaneo, Jansson, and Ma, 2020.

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