Frictions and the Effectiveness of Need-Based Financial Aid: Evidence from Michigan's Tuition Incentive Program*

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Abstract

This paper examines how information and administrative frictions mediate effects of a generous need-based scholarship in Michigan, the Tuition Incentive Program (TIP). TIP covers in-district community college tuition and fees, can be stacked on top of most other financial aid sources (such as the Federal Pell Grant), bases eligibility on categorical participation in Medicaid, does not require annual certification of need, and communicates eligibility early in students' academic career. Despite these advantageous features, participation in the program remains low. Reduced form-evidence shows null effects on enrollment for barely-eligible students, but a 3 to 4 percentage point increase for students with persistent signs of eligibility. To quantify the role of information, application, and compliance frictions as barriers, we develop and estimate a structural model of college choice and aid application, in which some students are unaware of the program. The model is calibrated to match the estimated reduced-form moments. Simulations show that the effect of TIP is more than doubled when these frictions are removed. Differences in information and administrative frictions across settings may thus explain some of the variation in financial aid treatment effects documented in the literature.

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1 Introduction

Many states have invested in college affordability via need-based financial aid or other "free college" programs to meet ambitious college attainment goals. At $16 billion in 2024, state grant programs now add up to half of that spent on the Federal Pell grant program [Ma et al., 2025]. These efforts are motivated by evidence that financial aid can increase college enrollment and completion [Dynarski et al., 2022, Denning et al., 2019, Bettinger et al., 2019, Angrist et al., 2022]. In an attempt to target aid to the most needy, however, many of these programs have complex and non-transparent eligibility criteria and require students to go through long administrative processes before they learn about or receive aid [Everett et al., 2024]. Many students may simply not know about or know how to access the aid they are entitled to or get tripped up when trying to receive it. Informational and administrative frictions might thus undercut the effectiveness of these interventions.

A consensus is emerging that high visibility, transparency about eligibility, simple administrative processes, an expectation for continued support, and timing coinciding with decision-making are crucial for aid to alter students choices [Dynarski and Scott-Clayton, 2013, Page and Scott-Clayton, 2016]. This consensus mostly comes from comparisons across studies that examine programs with different characteristics and set in different contexts. Several well-known Promise-type programs in Michigan, Pittsburgh, Oregon, and Tennessee have many of these characteristics and are among the most effective aid programs [Bartik et al., 2021, Page et al., 2019, Gurantz, 2020, Carruthers et al., 2020, Dynarski et al., 2021]. Evidence on the Federal Pell Grant program, which does not share these features, is mixed with positive effects in some settings [Denning et al., 2019] but not in others [Eng and Matsudaira, 2021, Carruthers and Welch, 2019]. At the same time, a consensus is also emerging that interventions that simply provide potential recipients of financial aid with information do not substantially alter student decision making [Bergman et al., 2019, Burland et al., 2023], but those that simplify the application process, by providing assistance to students as they navigate complex aid application processes, for instance, have greater impacts on college enrollment [Bettinger et al., 2012]. To date, however, we lack evidence on the extent to which these two sources of frictions– information and administrative barriers– hinder access to aid and how the alleviation of these frictions impacts college enrollment decisions within the context of a single aid program.

This paper fills this gap in the literature, combining reduced-form and structural approaches. We investigate the historically largest need-based state aid program in Michigan over the past decade, the Tuition Incentive Program (TIP), which distributed $118 million to nearly 40,000 students in 2024-25 [Michigan Department of Lifelong Education, Advancement, and Potential, 2026]. TIP provides a first-dollar scholarship that covers in-district community college tuition and fees and more limited aid at four-year institutions

for disadvantaged students. The average amount of TIP aid is close to $2700 annually among those that receive it. This aid can be stacked on top of the Federal Pell Grant and students are made aware of their eligibility as early as sixth grade. Eligibility is primarily based on Medicaid participation prior to high school graduation and, unlike most need-based programs, students do not need to certify need annually in order to continue to receive it.

Despite these desirable features, take-up of the TIP scholarship is low; only 30% of students that are enrolled in community college and are TIP-eligible actually receive it. We document the proximate reasons for this in a companion mixed-methods study [Burland et al., 2025], including inconsistent information about students' eligibility, confusion about interactions between TIP and other aid, variation in high school counselors' understanding of the program and access to student eligibility, and numerous administrative and technical hurdles. TIP is thus similar to other safety net, transfer, and social insurance programs such as Temporary Assistance for Needy Families (TANF), Medicaid, and Unemployment Insurance (UI), many of which also suffer from incomplete take-up [Currie, 2006, Ko and Moffitt, 2022] due to information and administrative barriers [Herd and Moynihan, 2019].

We estimate the effect of TIP eligibility on college enrollment using administrative data following eleven cohorts of public high school graduates in the state and two complementary reduced-form approaches. First, we use a regression discontinuity (RD) design, taking advantage of the fact that students are eligible for TIP if they received Medicaid for at least 24 within a 36 consecutive month period from age nine until high school graduation. While eligible and ineligible students differ on many dimensions likely to be correlated with college enrollment (SAT/ACT scores, race, special education status, poverty status), these differences disappear when comparing barely eligible vs. barely ineligible students. Students that just meet the 24-month requirement are 3.5 percentage points more likely to receive TIP and receive $221 more dollars in TIP aid within two years of graduating high school than those who barely do not qualify. These estimates represent a sizable increase given that many students do not enroll in college, enroll in a non-eligible institution, or do not receive TIP even if they enroll and are eligible; the two-year cumulative award amount is $ 6314 among those that receive TIP. However, for students near the threshold, few eligible students take-up TIP (less than 10%), and eligibility for TIP is not systematically associated with college enrollment.

Our second approach compares students that have a similar level of disadvantage during childhood, but differ in their TIP eligibility due to the precise timing of their participation in Medicaid. For instance, we compare students whose Medicaid participation was at younger ages or was more sporadic (not TIP eligible) to those consistently eligible during the right age (TIP eligible). Controlling flexibly for months on Medicaid during childhood balances other observed characteristics between TIP eligible and ineligible students. This approach provides an average treatment effect for a broader population than the RD approach, but

requires the stronger assumption that total time on Medicaid accounts for selection into treatment. Using this approach, we find that eligibility is associated with a 6.7 percentage point increase in likelihood of receiving TIP and $360 increase in TIP received. Eligible students are 3-4 percentage points more likely to enroll in college, with larger effects for students that spend more time on Medicaid in childhood. Effects of eligibility are much smaller for students with the minimum number of months on Medicaid needed to qualify for TIP, consistent with the findings from the RD approach.

We reconcile these findings by noting that these different approaches identify effects of TIP eligibility for different populations who likely vary in their awareness of the program. The RD approach isolates outcomes specifically among those near the eligibility threshold, which represents only a small share (less than 10%) of all TIP-eligible individuals. This may be a group that is particularly uninformed about the program and their eligibility; students with exactly 24 months of Medicaid (who barely qualify for TIP) have a take-up rate that is only a third as high as those students who are continuously enrolled in Medicaid. [Burland et al., 2025] suggests that students with greater attachment to Medicaid are more likely to have learned about TIP and their eligibility for it.

Could a reduction in information frictions, application costs, and administrative hurdles ensure TIP has a greater impact on enrollment? To answer this, in the second half of the paper we develop and estimate a structural model of financial aid application, college choice, and TIP take-up. A key feature is the inclusion of heterogeneity in information about TIP, the costs of applying for it, and the difficulty of completing the take-up process. We estimate the model within a GMM framework that combines score-based moments from the likelihood with auxiliary reduced-form moments from the first half of the paper. The estimation also uses a contraction mapping to recover college-specific mean utility differences.

The estimates explain why a generous aid program can have muted effects for some students and larger effects for others. Near the eligibility threshold, only about 48% of students are predicted to be informed about TIP, while the average informed share among eligible students is much higher because information rises steeply with Medicaid exposure. The model fits the moments most central to this interpretation: it closely matches the Medicaid gradient in the matching design and the pooled school-level application rate. Counterfactual simulations then show that the baseline effect of TIP is 3.49 percentage points for community college enrollment and 3.65 percentage points for total enrollment, but these effects would rise to 11.26 and 9.70 percentage points in a frictionless program. Information frictions are important for barely-eligible students, but application and compliance frictions are significant for all students.

The structural results turn the reduced-form contrast between the RD and matching estimates into a policy decomposition: information matters most near the threshold, while application and administrative frictions substantially limit the program's overall effect.

These results are also consistent with a growing consensus in the financial aid literature that information interventions alone may have little impact on enrollment, while interventions that reduce administrative frictions have greater impacts: while information might matter a great deal for those near the eligibility cut-off, if few eligible students are near the eligibility cut-off (as in the case of TIP), then there is less room for information to have a substantial impact on college enrollment decisions among the broader population.

This work contributes to the growing body of evidence on the effects of financial aid on student outcomes (see Dynarski et al., 2022 for a review). We contribute to this literature by focusing on a program that has many of the features of a model aid program, but in which information or administrative frictions still impede effectiveness. We show how the alleviation of these can improve program effectiveness. This contributes to work that shows that information frictions are often more costly for low income households when making high-stakes choices [Hastings and Weinstein, 2008, Hoxby and Turner, 2013, 2015, Andrabi et al., 2017, Arteaga et al., 2022] and that which adopts a structural framework to estimate misinformation costs and potential solutions [Allende et al., 2019, Kapor et al., 2020, Arteaga et al., 2022, Agte et al., 2024]. The issue also relates to a lack of price transparency seen in many industries, including health care, cell phones, and insurance [Brown, 2019, Grubb and Osborne, 2015, Ho et al., 2016]. Ours is the first to develop a model informed by reduced-form estimates to quantify how information and administrative frictions mediate the effect of need-based student aid.

The next section provides background on the policy context and prior literature. Section III describes our data sources. Section IV presents our two reduced-form approaches to evaluating TIP, evidence for their validity, and results. Section V presents a reduced-form choice model suggesting that lack of information about TIP undermines its role in altering enrollment decisions. We use this to motivate our structural model, which we present in Section VI and estimate in Section VII. Section VIII reports counterfactual simulations, and Section IX concludes.

2 Prior Evidence and Policy Background

2.1 Financial Aid and College Enrollment

Financial aid to reduce the price that students pay for college has been one of the main strategies policymakers have used to increase college enrollment and completion and close persistent socioeconomic gaps in these [Bailey and Dynarski, 2011]. Research largely shows positive effects on enrollment of increasing financial aid [Dynarski and Scott-Clayton, 2013, Page and Scott-Clayton, 2016, Dynarski et al., 2022, Goldrick-Rab et al., 2016, Nguyen et al., 2019], and a negative relationship between high levels of debt and persistence to degree [Dwyer et al., 2012]. Denning et al. [2019] use a regression discontinuity approach

to show that students who marginally qualify for the maximum federal Pell Grant in Texas are significantly more likely to complete college, and have higher earnings after graduation, compared to students who barely don't qualify. Eligibility for need-based aid in California was associated with greater undergraduate and graduate degree completion [Bettinger et al., 2019]. Other studies of the Pell grant, however, find mixed or null effects of additional grant aid more broadly [Eng and Matsudaira, 2021], likely due to administrative challenges [Carruthers and Welch, 2019].

Evaluations of free-college programs indicate large enrollment increases after tuition costs were eliminated in Oregon [Gurantz, 2020], Pittsburgh [Page et al., 2019], and Tennessee [Carruthers et al., 2020]. However, these programs vary substantially in their structure [Perna and Leigh, 2018], and have faced criticism for creating additional barriers for low-income students to complete degrees. For instance, many limit aid to two-year institutions, only cover tuition rather than the full cost of attendance (excluding food and housing), have complicated application processes, or can get crowded-out by other aid. It is perhaps not surprising that the Kalamazoo Promise, which covers tuition and fees at any in-state college with minimal process barriers, increased enrollment at a four-year college by 6 percentage points and BA completion by 7 percentage points [Bartik et al., 2021].

Beyond the dollar value of financial aid programs, the details of these programs matter for how they affect college enrollment and completion. For instance, research on the federal education tax credits finds no effect on college enrollment because their benefits are non-transparent and come too late to influence choices [Bulman and Hoxby, 2015]. Outreach programs that inform students about their potential eligibility for tax credits also do not affect enrollment, suggesting that information constraints alone do not prevent students from accessing this form of aid [Bergman et al., 2019].

Restrictions on where the aid can be used may also influence the effect of financial aid programs. Programs limited to two-year institutions may have the unintended effect of shifting students who would have otherwise enrolled in four-year institutions into community colleges, which could lead to lower college completion rates [Carruthers et al., 2020, Goodman et al., 2017, Smith and Stange, 2016, Cohodes and Goodman, 2014]. Policies that target four-year institutions could also lead to adverse outcomes, depending on the counterfactual college landscape. Cohodes and Goodman [2014] found that the Adams Scholarship in Massachusetts lowered college completion rates by diverting high-achieving students away from more selective institutions, with higher student spending and higher graduation rates, into less-selective institutions. Conversely, Denning [2017] shows positive college enrollment effects of reducing community college tuition in Texas, with no negative effects on subsequent college completion or four-year transfer rates.

The administrative details of financial aid programs are also important for their efficacy [Perna et al., 2020]. Literature on the effects of education interventions on college outcomes

identifies several key lessons for designing effective financial aid policies: providing clear eligibility guidelines, simplifying the application process, and notifying students about their eligibility early, before the college application process begins. In contrast, interventions that simply inform students about existing aid or the college enrollment process, without simplifying the process itself, largely find no effects on college outcomes [e.g. Bergman et al., 2019, Gurantz et al., 2021, Hyman, 2020]. Interventions that simplify the application process have proven far more effective in increasing college enrollment, particularly among low-income students. For instance, a study of H&R Block tax clients found that helping families fill out financial aid forms resulted in large increases in college enrollment, whereas merely telling families about how to file financial aid forms had no effect [Bettinger et al., 2012].

A randomized controlled trial in Michigan that provided an early, targeted guarantee of four years of free tuition to attend the University of Michigan doubled college enrollment and persistence among low-income, high-achieving students [Dynarski et al., 2021]. Importantly, the intervention did not increase the amount of aid that students would have qualified for under the traditional financial aid system, but guaranteed the aid upfront, without requiring students to complete financial aid forms. The key takeaway from that intervention pointed to the importance of a clear, upfront guarantee of aid prior to the college application decision as well as the removal of administrative hurdles to determine eligibility.

We contribute to this literature by examining the effects of a large need-based aid program in Michigan that has several of these desirable design features, as we describe below.

2.2 Michigan's Tuition Incentive Program (TIP)

We examine college-going and affordability in the State of Michigan, which set an ambitious college attainment goal: 60% of adults obtain a postsecondary degree or credential by 2030, which is dubbed "Sixty by 30." The state has identified the cost of college as one potential barrier to achieving this goal. In response, the state has invested considerably in student aid. In 2024-2025, the state invested more than $558 million to help nearly 154,000 students afford college through a series of long-standing financial aid programs [Michigan Department of Lifelong Education, Advancement, and Potential, 2026]. Recent efforts by the state have made community college tuition-free for frontline workers, adults over the age of 25 (and, temporarily, even younger), and now nearly everyone through the Community College Guarantee. These state aid programs complement various place-based scholarship programs in many communities around the state, along with funding given directly to institutions to offset the cost of tuition. Historically, TIP is the most significant of these programs, covering tuition and fees (up to a limit) at in-district community colleges for low-income students enrolled in certificate and associate degree programs (referred to as "Phase I" and the focus of our analysis). TIP also provides up to $500 per semester to students attending four-year

institutions, but only after they have earned a certificate, associate degree, or 56 transferable semester credits ("Phase II"). Until recently, TIP was the largest scholarship program in the state, awarding more than $118 million to nearly 40,000 students in 2024-2025, with an average annual aid amount of $2,980.[1]

Eligibility for TIP is based primarily on need. Students must have been covered by the state's Medicaid program in at least 24 of 36 consecutive months from age nine until high school graduation. Medicaid eligibility is based on family income, with families earning less than 212% of the federal poverty level eligible (plus other categorical criteria). Students must also be a Michigan resident, be a US citizen or permanent resident or refugee, possess a high school diploma or equivalent prior to age 20, and not have defaulted on a Federal student loan. To actually receive TIP, students must file a FAFSA form. Prior to 2021, students were also required to complete a separate TIP application form prior to August 31st of the year they graduated high school. Finally, students must be enrolled at least half time at a participating institution and begin using TIP within four years of high school graduation. Students can continue to receive TIP for up to ten years.

TIP's design is notable in several ways. First, it is one of only a few large scholarship programs directly linked with participation in a social safety net program. Students are need-eligible for TIP if they meet this Medicaid requirement, and there are no other income or asset tests. Eligibility thus relies on administrative data linkages, potentially reducing uncertainty surrounding eligibility and eliminating the need for students to verify their income. Because of the size of the low and moderate-income population in Michigan, as well as the recent Medicaid expansion as part of the Affordable Care Act (ACA) in 2014, each year approximately 40% of high school seniors meet the eligibility criteria for TIP.

Second, eligibility is fixed throughout college and there is no need for students to continue to verify or prove their eligibility each year. This contrasts with most aid programs, including the Federal Pell grant, which relies on an annual need assessment via the FAFSA. Many research studies examine students at the edge of eligibility which, combined with the need to re-certify need annually, means they mostly examine the effect of the scholarship on aid received in the first year [Denning et al., 2019, Castleman and Long, 2016]. Guaranteed aid has been shown to be effective at boosting college enrollment and completion [Dynarski et al., 2021]. TIP guarantees aid for up to ten years regardless of students' changing economic circumstances.

Third, students can become eligible and be informed at a young age, as early as 6th grade. Early awareness that college is affordable may alter student course-taking decisions, academic performance in courses and standardized tests, preparation for college, and potentially high school completion [Bartik and Lachowska, 2013, Ash et al., 2021]. Our study will illuminate

[1]TIP Phase I can actually be used for certificate and associate degree programs at certain private and four-year colleges as well, though community colleges represent the vast majority of funding and students. Program details can be found at https://www.michigan.gov/mistudentaid/programs/tuition-incentive-program.

an understudied question about the impact of informing students of their eligibility for financial aid as early as middle school, and how this affects college decision making. Given that the college-going culture and rates of financial aid application at a student's high school can influence college application and attendance behavior [Roderick et al., 2011], early notice of eligibility may have a different effect on students than programs that notify at the conclusion of high school.

Finally, TIP is a first-dollar scholarship, which means that students can use the funding to pay for tuition, freeing up other forms of financial aid, like Pell Grants, to pay for books and living expenses. In contrast, many state "free college" programs are structured as last-dollar scholarships (e.g. New York's Excelsior Scholarship, the Oregon Promise program). Such programs often do not provide benefits to the lowest-income students attending community colleges, since much of their tuition expenses are covered by the Pell Grant. As small and generous place-based scholarship programs have been scaled up to state-wide programs, this useful feature has been lost, potentially muting the aid's effectiveness. As a previously unevaluated program, TIP represents an opportunity to causally estimate the effects a first-dollar program at scale, which Nguyen et al. [2019] emphasize is an important avenue for empirical assessment of factors that affect student outcomes.

These four policy attributes - categorical, guaranteed, early, and first-dollar - make TIP similar to some of the highly effective place-based scholarships, such as the Kalamazoo Promise, which substantially increased college enrollment and attainment [Bartik et al., 2021]. It may offer a model for how states could scale up other free tuition programs [Brown et al., 2021], given the importance of details of financial aid programs for their efficacy [Perna et al., 2020].

Despite the many good design features described above, various administrative and informational barriers have historically impeded TIP take-up, which we explore in a companion paper [Burland et al., 2025]. Additionally, the State of Michigan has made significant changes which may improve TIP take-up recently, including removing the requirement for a separate TIP application, increasing student outreach, and implementing a new universal scholarship that may "crowd-in" use of TIP. A large increase in TIP volume in 2023-2024 relative to the prior year suggests some of these efforts may be paying off. Our analysis focuses on a time period when many of these informational and administrative barriers still existed.

3 Data and Sample

3.1 Data Sources

We combine data from several administrative sources. From the Michigan Department of Education (MDE) and Center for Educational Performance and Information (CEPI),

we assemble K12 education records, including attendance, high school attainment, demographics, test scores, free lunch eligibility, and addresses for all elementary and secondary students in Michigan public schools since 2003. These records permit us to construct our population, as well as characterize their academic and socioeconomic backgrounds in primary and secondary schools. K12 records are linked to the National Student Clearinghouse (NSC), which tracks enrollment and degree attainment for 95% of US undergraduates. NSC-derived measures of college attendance will be our main outcomes. Importantly, NSC includes private schools and schools outside Michigan in addition to public institutions in Michigan, which ensures there will be no attrition from our main college outcomes. For students that attend the state's public post-secondary institutions since 2011, we also have college transcripts which we use to construct measures of credits attempted and earned, as well as indicators for Pell grant recipients.

From the Michigan Department of Lifelong Education, Advancement, and Potential (MiLEAP), we merge information about participation in and amount received in all student aid programs administered by the State of Michigan. These include TIP, but also the Michigan Tuition Grant (MTG, for private colleges), Michigan Competitive Scholarship (MCS, merit-based), small targeted programs (foster youth, children of veterans) and, since 2023, the Michigan Achievement Scholarship (MAS, broad-based scholarship for many students). This data permits us to characterize how TIP eligibility may alter financial aid from all state sources. Finally, from the Michigan Department of Health and Human Services (MHHS) we obtain indicators for Medicaid enrollment in each month, as well as monthly enrollment in TANF and SNAP. We estimate TIP eligibility using these monthly Medicaid enrollment records. MDHHS records are matched by the Michigan Education Data Center staff to student records based on name and date of birth with over 90% of MDHHS records matched in the education data. This permits us to construct a measure of the number of months on Medicaid in each 36 month window before graduation, which determines TIP eligibility.

The rich administrative data is also combined with publicly available data on college characteristics (posted tuition prices, spending per student, sector) and community characteristics (e.g. share of residents with college degree, average income) from IPEDS and the US Census, respectively.

3.2 Sample

Our primary sample is eleven cohorts of high school graduates from Michigan's public high schools from 2011 to 2021. We limit the sample to high school graduates because TIP requires students to earn a high school diploma or its recognized equivalent prior to age 20.[2]

[2]By guaranteeing tuition-free community college, it is possible that TIP eligibility may induce greater effort during high school or even increase high school graduation rates. These effects are important avenues for future

Our full sample includes nearly 1.2 million unique students. Table 1 reports characteristics of our full sample in column (1). Across all years approximately 34% are Medicaid-eligible for TIP. Nearly three-quarters of grads enroll in some kind of postsecondary institution within the first two years after high school, with 39% enrolled in a Michigan community college. Overall, 4% of students earn an AA within three years of high school graduation and one third earn a BA degree within 6 years.

The next two columns divide the sample into those that do not meet the Medicaid participation threshold and are thus not eligible for TIP (column 2) and those that do (column 3).[3] Eligible and ineligible students differ on many dimensions likely to be correlated with college enrollment. For instance, eligible students have much lower ACT scores than ineligible students (18 vs. 21) and are much more likely to be in poverty during high school (71% vs 20%). Eligible students are more likely to be African American or Hispanic than ineligible students.

These differences largely disappear when comparing students that barely meet the eligibility threshold of 24 months (column 5) vs. those that barely miss it (column 4). The share in poverty and average ACT score are nearly identical for students with 22 or 23 months of Medicaid and those with 24 or 25 months, though these groups differ in their eligibility for TIP.

4 Reduced Form Evidence of Program Effects

We estimate effects of TIP on enrollment using two complementary reduced-form approaches. Our first approach exploits the feature that eligibility for TIP depends on monthly Medicaid enrollment in a way that facilitates a regression discontinuity (RD) design, comparing students that are barely eligible to those barely ineligible for TIP. This approach estimates an average treatment effect for the local population near the eligibility cutoff who, based on our prior work, may be particularly uninformed about the program. We thus also implement a matching approach whereby we compare students with a similar level of disadvantage in childhood (measured by months enrolled in Medicaid), but who differ in TIP eligibility due to the timing of that enrollment. This permits us to examine a broader population further from the eligibility threshold.

4.1 Regression Discontinuity Approach and Validity

We first estimate the effect of TIP eligibility on aid received and educational outcomes using a regression discontinuity (RD), comparing students barely eligible to barely ineligible for TIP.

work.

[3]Note that a small number of students that appear TIP ineligible are observed receiving TIP. This could be due to errors in the matching procedure used to link across data sources or appeals/petitions related to eligibility that we do not observe in our data.

The running variable $MedicaidMonthsRV_i$ is the maximum number of months enrolled in Medicaid across all 36 month windows between the student's ninth birthday and high school graduation. Students for which this number exceeds 24 are eligible for TIP. Figure 1 shows the rate of TIP receipt separately by $MedicaidMonthsRV_i$. As expected, receipt of TIP increases considerably as students pass the 24-month threshold, though take-up is quite low. Interestingly, participation increases steeply with $MedicaidMonthsRV_i$ and is much higher for those who have a 36-month spell on Medicaid than those barely eligible for TIP. We return to this pattern in the discussion below.

We estimate regression models of the form:

$$Y_i = \beta TIPElig_i + f(MedicaidMonthsRV_i) + \varepsilon_i \tag{1}$$

Where Y_i is an outcome of interest, such as college enrollment, $TIPElig_i$ is a dummy variable indicating the student is eligible for the TIP program when they graduate from high school based on their Medicaid enrollment history, and ε_i is a residual. The term $f(MedicaidMonthsRV_i)$is a flexible function capturing the relationship between months of Medicaid enrollment and the outcome, separate from the TIP eligibility. Importantly, we observe outcome and treatment information for all students enrolled in Michigan public schools, not just those who were ever on Medicaid, so there are no attrition concerns in our sample. With no mismeasurement of eligibility, this would be a sharp RD design since all students with fewer than 24 months of Medicaid receipt would not be eligible for TIP, and all students with at least 24 months of Medicaid receipt would be eligible. In practice, we likely measure eligibility and Medicaid months with error due to matching issues, inconsistencies across data bases, and a lack of information about other elements of eligibility (e.g. immigration status). We thus have a fuzzy RD, whereby true eligibility for TIP changes discontinuously (but incompletely) across the threshold.

The parameter of interest is β, which we interpret as the causal effect of being eligible for TIP. This parameter captures the "intent to treat" of being eligible for TIP, but it does not isolate the effect of receiving the scholarship, since many eligible students will not receive the scholarship. Non-receipt can occur for several reasons - not enrolling, attending an ineligible institution, failing to file a FAFSA or TIP application, or information disconnects between the institution and the awarding agency. We cannot distinguish these channels, which are endogenous, so we focus on intent-to-treat estimates. Furthermore, as noted above, TIP eligibility is a multi-faceted treatment, combining financial incentives (tuition and fees) with outreach on the part of the MiLEAP Office of Higher Education and its predecessor. Since we do not have separate instruments for each of these distinct "treatments" embedded in TIP eligibility, we focus on the combined intent-to-treat effect of TIP eligibility. Furthermore, this approach identifies the effect of TIP eligibility for students whose Medicaid enrollment patterns put them close to the eligibility threshold, but does not necessarily generalize

away from the threshold. It is possible that the effect of financial aid is different for higher-income students (zero years of Medicaid coverage) or lower-income students (with persistent Medicaid eligibility), which we would not be able to discern with this research design.

We employ the procedures developed by Imbens and Kalyanaraman [2012] and Calonico et al. [2014] for MSE-optimal bandwidth selection. Our base model uses local linear regressions where the slope differs across the TIP eligibility threshold, as well as a triangular kernel which gives more weight to observations closer to the threshold, though we examine the robustness to alternative specifications. To interpret this comparison causally, we must assume that there are no other differences between students that received Medicaid for 24 months compared to those who received it for 23, other than eligibility for TIP, in ways that correlate with outcomes.

In order to test for observable differences across the threshold, we run balance checks by estimating equation (1) but with baseline student characteristics as the outcome, including sex, race, test scores, and safety net usage. These tests, reported in Appendix Table A1, reveal few observable differences between students near the eligibility threshold and differences that do exist are small in magnitude. The only two statistically significant differences we see are in share female and months on TANF. In particular, those who are barely eligible for TIP are 3pp less likely to be female and have received TANF for 0.7 fewer months than those who are Medicaid-eligible for TIP. We do not know of any institutional or policy characteristics that could have generated these patterns. Nonetheless, they are small in magnitude and would be expected to have opposite effects on the patterns we study (women are more likely to enroll in college, while TANF receipt is associated with lower levels of enrollment). Our conclusions about the outcome consequences of TIP are unchanged if we control for these characteristics or not.

Even if students have similar observable characteristics across the discontinuity, it is possible that students may differ in unobservable ways if they can sort themselves across the threshold. For instance, students (or their parents) who know where they stand relative to the 24 month threshold may be particularly motivated to ensure continued Medicaid coverage so as to reach TIP eligibility and receive free college tuition. This unseen motivation may also influence enrollment, persistence, and degree completion. In this case, it would be impossible to separate the effect of these unobservable traits from the direct effects of TIP eligibility. The typical way to test for this is to observe whether there is bunching of the sample right above the threshold, which may be indicative of manipulation that could threaten exogeneity [McCrary, 2008]. Appendix Figure A1 depicts a histogram of our relevant running variable: the max number of months that a student receives Medicaid in any given 36 consecutive month periods from age 9 until HS graduation. We omit the mass at zero months (60% of sample) and 36 months (27%) for clarity. There is some bunching around common months

such as 12 months, 15 months, 24 months (our threshold), and 36 months. This is not necessarily evidence of manipulation, as Medicaid tends to be renewed annually, so multiples of 12 months is expected. This will generate bunching at 12 months, 24 months, and 36 months. This is somewhat analogous to a 3.0 GPA cutoff in some educational RD studies, which can often be defended from any concerns about manipulation by arguing that B is a very common grade, leading to bunching. We demonstrate that our results are robust to excluding students with exactly 12, 24, and 36 months [Barreca et al., 2016].

4.2 Effect of TIP Eligibility Among Barely Eligible

Tables 2 and 3 report our preferred RD estimates using the optimal bandwidth, triangular kernel, and no controls. Table 2 reports effects on financial aid receipt. We see that there is a clear effect of becoming eligible for TIP on receipt of TIP. Crossing the threshold for TIP eligibility leads to a 3.5pp increase in TIP 1 take-up within two years of HS graduation. An increase of roughly 3.5pp corresponds to 25% of the baseline take-up rate of 14% among all HS graduates. Crossing the eligibility threshold leads to a $221 increase in TIP amount (in 2019 USD) by year two. Note that these magnitudes include the large number of TIP-eligible students that do not receive TIP; the scholarship amount among those that receive TIP is approximately $2700 per year. Finally, total financial aid from the State of Michigan increases approximately by the amount of TIP - $248 by year two. Furthermore, we do not see a statistically significant crowd-out (or crowd-in) of the Federal Pell grant among those newly eligible for TIP, though the point estimate is negative.

Figure 2 displays enrollment outcomes within two years of high school graduation, separately by the running variable. There is not an noticeable change in enrollment overall or in any sector across the eligibility threshold. Table 3 reports corresponding point estimates over different time horizons since HS graduation. Overall, we find no impacts on enrollment over any time period. This is consistent with some prior work that found minimal effects of the Pell grant on enrollment among four-year college students [Denning et al., 2019]. Given that TIP Phase I primarily targets in-district community colleges, we also consider differential impacts of TIP eligibility on enrollment at two- and four-year colleges. For example, it is plausible that TIP could induce more students to attend a two-year college, either from no college at all or from a four-year college. However, we find no effects on enrollment in any sector.

Our conclusion of minimal enrollment effect of TIP eligibility is robust to alternative specifications, including changes in the bandwidth, kernel, and inclusion of controls. In fact, for any reasonable bandwidth, our point estimates are negative and statistically insignificant. These results are reported in Appendix Table A2. Finally, Cattaneo et al. [2024] suggest randomization-based (rather than continuity-based) test when the running variable is finite, as in our setting. This approach effectively compares the enrollment rate for [22,23] vs.

[24,25], a difference of -0.001 (p = 0.920).

4.3 Matching Approach and Validation

Though credible, the RD approach identifies the effect of TIP eligibility for the specific population of students close to the eligibility threshold. This may be a group that is particularly uninformed about eligibility; Figure 1 shows that students with exactly 24 months of Medicaid (who barely qualify for TIP) have a take-up rate much lower than those students who are continuously enrolled in Medicaid. Our RD estimates may thus provide a misleading picture of the effect of TIP eligibility more generally.

There have been methods developed in the RD literature to estimate treatment effects for individuals located further away from the RD cutoff. For instance, Angrist and Rokkanen [2015] use a conditional independence assumption, where the researcher can fully account for the correlation between the running variable and the outcome of interest using observable characteristics, to make inference away from the RD cut off. Unfortunately, this assumption fails in our context: our covariates are insufficient to fully account for the relationship between the running variable and the outcomes of interest.

Battistin and Rettore [2008] provide an alternative test for making causal inference away from the cut-off in fuzzy RD settings where take-up of the treatment is incomplete. The method essentially tests for selection bias into participation in a given program around the RD cut-off, and argues that if selection bias around the cut-off can be explained by covariates, one can make inference away from the RD cut-off. Unfortunately, our setting does not neatly fit into the criteria required for Battistin and Rettore [2008] because participation in TIP requires college enrollment (our outcome of interest), which leads to negative selection when identifying eligible non-participants.

Since neither of these tests neatly applies to our context, we take advantage of a different quirk in determining eligibility for TIP: receipt of Medicaid must take place between ages 9 and high school graduation and individuals must be on Medicaid for at least 24 months within a 36 month time window. Leveraging these additional constraints on eligibility, we compare outcomes of HS grads who have the same *total* months on Medicaid throughout childhood, but differ in TIP eligibility due to differences in the *timing* of Medicaid enrollment during childhood. For instance, whether these months come before vs. after age 9 or whether they fall within a consecutive 36 month window.

We implement this by regressing our outcome on TIP eligibility and indicators for each unique number of total months of Medicaid, along with cohort fixed effects and other covariates.

$$Y_i = \beta TIPElig_i + \sum_{k=0}^{96} \delta_k (TotalMedicaidMonths_i = k) + \gamma_t + \Gamma X_i + \varepsilon_i \qquad (2)$$

Comparisons are made between students that have, for instance, 36 total months on Medicaid during childhood, but the timing of those months differs resulting in differential TIP eligibility. This approach estimates a treatment effect for a broader population, but requires the strong assumption that months on Medicaid during childhood sufficiently controls for selection into treatment. We restrict analysis to students with at least 24 total months of Medicaid enrollment during childhood so that TIP eligibility is a possibility. We also exclude students with more than 96 months as nearly everyone in this category is eligible.

The variation in Medicaid enrollment underlying this strategy is illustrated in Appendix Figure A2. Among students that have exactly 36 months of Medicaid enrollment before high school graduation, some are not eligible for TIP because these months do not fall close enough together to accumulate to 24 months within a 36 month window. Those ineligible are more likely to have multiple and shorter spells of Medicaid enrollment. In some specifications we thus include controls for the number of spells.

If the total number of months on Medicaid was a sufficient proxy for economic disadvantage that we worry is correlated with both TIP eligibility and outcomes, then TIP eligibility should be uncorrelated with other student characteristics after we've conditioned on total months. We implement this balancing test by regressing versions of equation (2) using covariates as the outcome. The results from this exercise are shown in Table A3 in the Appendix. While TIP eligible students are different than ineligible students - they spend more years on free-or-reduced price lunch, have lower SAT scores, and slightly less likely to be female or Black - these differences diminish greatly once the total months on Medicaid is controlled for non-parametrically. For instance, TIP eligible students have a 12 percentage point higher share of years on free or reduced-price lunch and score 8 points lower on the SAT compared to TIP ineligible students among this already restricted sample. These differences disappear when we control flexibly for months on Medicaid and number of Medicaid spells. We examine two different measures of total months on Medicaid - total since birth and since age 9 (corresponding to the ages that determine TIP eligibility) - which we use in isolation and also together.

4.4 Effect of TIP Eligibility Using Matching

Figure 3 illustrates our matching approach - and conclusion - graphically. The figure plots the total TIP amount received (top panel) and the share of students that enroll in college within two years of high school (bottom panel), separately by the total number of months on Medicaid and by TIP eligibility. Unsurprisingly, TIP eligible students receive higher TIP amounts than ineligible students with a similar number of months on Medicaid.[4] In

[4]Recall that our eligibility imputation is imperfect, so a small number of "ineligible" students are likely eligible and thus receive TIP. Importantly, this phenomenon does not appear to be correlated with our measured months on Medicaid.

the bottom panel, we see that eligible students have higher rates of college enrollment at almost all points on the distribution of months on Medicaid. Note that college enrollment overall is steeply decreasing in months on Medicaid - unsurprising given that economic disadvantage (of which months on Medicaid is a proxy) is strongly related to non-enrollment in college. Interestingly, the gap between eligible and ineligible students grows as months on Medicaid increases. TIP eligiblity thus appears to flatten the well-known SES-college enrollment gradient, at least among people that have a moderate amount of engagement in the social safety net.

Table 4 reports the estimates from equation (2) for various specifications. After controlling flexibly for the number of months on Medicaid, TIP eligible students receive about $360 more in TIP amount after two years. Effects on college enrollment are universally positive and statistically significant across all specifications. Column (2) includes dummies for total months on Medicaid (24 to 96) throughout childhood. Here TIP eligibility is associated with a 2.4 percentage point higher rate of enrollment at any college. This estimate ranges between 3.2 and 4.0 when instead we use months on Medicaid since age 9 (column 3), include controls (column 4), or include a very saturated model with months since birth and since age 9 simultaneously (column 5). Treatment variation in the latter specification is driven by the precise timing and length of spells since age 9 above and beyond the general disadvantage predicted by pre-age-9 Mediciad and controls. Since individuals with only a single long spell (e.g. 24 months consecutively starting at age 9), who will all be TIP eligible, may be different than those with several spells, in column (6) we include dummies for the number of Medicaid spells since age 9. The estimate is still a large and significant 2.6 percentage points.

The last three rows of Table 4 report estimates for enrollment effects in different sectors. Effects are mostly concentrated in the public 2-year sector, with smaller effects at public 4-year colleges. While benefits are greatest at in-district community colleges, it can be used for some Associate's degree programs housed at a few 4-year colleges and more recently at some private colleges. Thus TIP increases the affordability of not just students' in-district community college.

Figure 3 showed that gap between TIP eligible and non-eligible grows with the level of disadvantage. To quantify this, Table 5 presents matching estimates from a model that interacts TIP eligibility with the number of months on Medicaid (Panel A) or separately by duration on Medicaid in six-month increments (Panels B through E). These models continue to include months on Medicaid (total and after age 9) flexibly, along with controls and dummies for the number of Medicaid spells. Using the full sample, we see that TIP eligibility is associated with a modest 1.3 percentage point estimated increase in enrollment for those minimally eligible. However, each additional year of exposure to Medicaid in childhood is associated with an additional 1.9 percentage point (= 12 times 0.155 ppt) greater enrollment

effect from TIP eligibility. This pattern is also seen in Panels B through E: the association between TIP eligibility and likelihood of attending college is monotonically increasing with childhood duration on Medicaid.

5 Do Information Frictions Impede Effects?

The contrasting reduced-form results present a puzzle. The RD approach finds no effect of TIP eligibility near the cutoff, while the matching approach reveals positive effects for students who are observationally similar yet differ in TIP eligibility. Take-up is lowest near the eligibility threshold and increases steeply with childhood Medicaid exposure. We hypothesize that information frictions explain this pattern: students at the RD threshold are less informed about TIP than those further from the threshold, whose deeper engagement with the safety net makes them more likely to have learned about the program.

We provide further evidence for this hypothesis using a simple discrete-choice model of college enrollment. Suppose student i considering college j observes the posted price p_j but has heterogeneous beliefs about the TIP aid available at college j, denoted a_{ij}:

$$u_{ij} = \beta_{\text{aid}} \underbrace{(-\mathbb{E}[a_{ij}])}_{\text{Initially Unknown}} + \underbrace{\beta_{\text{price}} p_j + \Gamma X_j + e_{ij}}_{\text{Known}}, \qquad e_{ij} \sim \text{EVT1}, \qquad u_{i0} = e_{i0}$$

If students are fully informed, then a dollar of financial aid and a dollar of tuition should enter symmetrically: $\beta_{\text{aid}} = -\beta_{\text{price}}$. Table 6 reports estimates from three specifications.[5] In all specifications, students respond negatively and significantly to posted tuition but respond weakly or inconsistently to TIP aid. We reject $\beta_{\text{aid}} = -\beta_{\text{price}}$ in every model. This asymmetry is consistent with several explanations: students may lack information about the aid available to them; receiving aid may require costly administrative steps such as completing the FAFSA or, prior to 2021, a separate TIP application; or administrative barriers may prevent eligible students from receiving aid even after enrolling.

To separate these channels and quantify the enrollment gains from addressing each, we turn to a structural model of information, application, and college choice. The reduced-form patterns—steeply increasing take-up with Medicaid exposure, null RD effects at the threshold, and positive matching effects away from the threshold—are naturally explained by a model in which the *share* of informed students varies with observables. Near the threshold, students have limited safety-net exposure and are disproportionately uninformed about TIP; further from the threshold, deeper engagement with social programs raises the likelihood of having learned about the program. The structural model decomposes TIP non-receipt

[5] We regress college choice on sticker price, TIP-eligible award amount, postsecondary institution fixed effects, and commuting zone–cohort fixed effects. Variation comes from cross-cohort changes in tuition and cross-student variation in TIP eligibility. Conditional logit models yield the same conclusion.

into three distinct channels—lack of information, application costs, and post-enrollment administrative challenges—and provides a framework for evaluating counterfactual policies that target each margin.

6 Structural Model

We develop a model of college choice with endogenous financial aid application and heterogeneous information. The model separates three channels through which TIP-eligible students fail to receive the scholarship: (i) lack of information about the program, (ii) hassle costs of applying, and (iii) post-enrollment administrative barriers to receipt. We describe each structural object in turn—a type probability governing who knows about TIP, an application cost determining whether informed students apply, and a receipt hazard capturing whether applicants successfully receive aid—before summarizing the full decision structure.

The companion qualitative and mixed-methods evidence motivates this sequence of frictions. Interviews with counselors show that many students do not learn about TIP through the official notification letter; awareness often arises through counselor intervention, peer or community familiarity, and repeated engagement with the safety net. The same evidence distinguishes awareness from application burdens: even students who know about TIP must complete the FAFSA and, before 2021, a separate TIP application. Finally, interviews with financial-aid staff show that receipt can fail after students apply and enroll because colleges must reconcile eligibility lists, billing records, FAFSA information, high-school graduation verification, residency, enrollment intensity, and aid-packaging rules [Burland et al., 2025, Thompson et al., 2025]. The variables below therefore map each structural shifter to a documented mechanism rather than treating non-receipt as a single residual friction.

6.1 Setup

Let $i \in \{1, \ldots, N\}$ index students, $j \in \{0, 1, \ldots, J\}$ index colleges (with $j = 0$ representing non-enrollment), $h(i)$ denote the high school attended by student i, and t denote the cohort year. The researcher observes enrollment choices $y_{ij} \in \{0, 1\}$ and TIP receipt $R_i \in \{0, 1\}$ for enrollees, along with Medicaid months m_i, published tuition p_{jt}, and the distance from home to each college d_{ij}. Let $\mathcal{J}^{TIP} \subset \{1, \ldots, J\}$ denote TIP-eligible colleges (Phase I community colleges and select four-year institutions) and A_{jt}^{rule} denote the deterministic TIP award schedule at college j in year t, which covers in-district tuition and fees, subject to upper limits.

6.2 Student Types

TIP-eligible students belong to one of two latent types: *Informed* (I) or *Uninformed* (U). Informed students know about TIP and its eligibility rules. They make an active decision about whether to apply and incorporate expected TIP aid into their college choice. Uninformed students do not know about TIP or have severely distorted beliefs about their eligibility; they do not apply and choose colleges ignoring TIP entirely.

The probability that student i is Informed is:

$$\pi_i^I \equiv \Pr(\tau_i = I \mid m_i, X_{h(i),t}) = \frac{\exp(\theta_0 + \theta_m \cdot m_i + \theta_X' X_{h(i),t})}{1 + \exp(\theta_0 + \theta_m \cdot m_i + \theta_X' X_{h(i),t})} \tag{3}$$

where m_i is the student's total months on Medicaid and $X_{h(i),t}$ includes counselor-to-pupil ratio, which proxies for the availability of guidance about financial aid programs at the high-school level. The parameter θ_m captures the effect of Medicaid exposure on awareness. We expect $\theta_m > 0$: students with longer Medicaid histories are more embedded in the social safety net and more likely to have learned about TIP through interactions with program administrators, counselors, or peers [Burland et al., 2025, Thompson et al., 2025].

This specification is guided by the companion evidence in two ways. First, Medicaid months proxy for safety-net embeddedness, not only economic need: students with more persistent Medicaid exposure have more repeated contact with benefit systems and with school personnel who may recognize TIP eligibility. Second, information is produced locally. Counselors vary in whether they can observe eligibility in the MiSSG portal, whether they proactively check student status, and whether they have enough capacity to explain TIP before college decisions are made. School-level $X_{h(i),t}$ therefore captures variation in the local information environment that determines whether categorical eligibility becomes salient to the student.[6]

This type structure directly operationalizes the patterns in the reduced-form evidence. The null RD effect arises because students near the 24-month threshold have low m_i and therefore low π_i^I—most are unaware of TIP, so eligibility has little effect on their choices. The positive matching estimates emerge because students further from the threshold have higher m_i, higher π_i^I, and thus respond to TIP eligibility.

[6] We also explored letting information vary based on the timing of eligibility. Like the companion evidence, students who became eligible in early high school had higher rates of being informed than those who learned earlier and later. These parameters are not precisely identified so we ultimately omitted them from the preferred model.

6.3 Preferences and College Choice

All students—regardless of type—share the same underlying preferences over colleges. The indirect utility that student i obtains from attending college j in year t is:

$$V_{ij} = -\gamma_i \cdot \tilde{p}_{ijt} + \phi \cdot d_{ij} + \sum_{\text{s(j)}\in\{\text{2y,4y,UM}\}} \alpha^{SES}_{s(j)} \cdot \mathbb{1}(s(j)=1) \cdot \text{HSpoverty}_i + \sum_{\text{s(j)}\in\{\text{2y,4y,UM}\}} \alpha^{test}_{s(j)} \cdot \mathbb{1}(s(j)=1) \cdot \text{Test}_i + \delta_{jt} + \varepsilon_{ij} \quad (4)$$

where $\tilde{p}_{ijt}$ is the effective price faced by the student (which depends on type and application status, as described below) and ϕ captures distance preferences. We include interactions between sector (2-year, 4-year(all), 4-year(+UM), all relative to non-enrollment) and students' test scores and socioeconomic status. These utility shifters account for selective admissions, as well as unobserved preferences and potential non-TIP aid which may correlate with both enrollment and SES and/or test scores. The vector δ_{jt} is the mean utility of college j in year t, collecting the effects of observable college characteristics, time-invariant quality, and transitory demand shocks: $\delta_{jt} = \beta_X X_{jt} + \xi_j + \xi_t + \Delta\xi_{jt}$. The taste shock ε_{ij} is i.i.d. Type 1 Extreme Value, yielding logit choice probabilities within each information and application state.

The marginal utility of money γ_i varies across students as a function of socioeconomic status:

$$\gamma_i = \gamma + \Gamma_{SES} \cdot \text{HSpoverty}_i + \Gamma_{test} \cdot \text{Test}_i \quad (5)$$

where HSpoverty_i is an indicator for being eligible for free or reduced-price lunch during high school. Test_i is students' normalized ACT or SAT score. This specification allows low-income students to be more price-sensitive, consistent with the intuition that the marginal utility of a dollar of tuition reduction is larger for students with fewer financial resources. The qualitative evidence supports this heterogeneity by emphasizing that TIP-eligible students face material resource constraints beyond posted tuition, including transportation, books, housing, and uncertainty about how aid packages are assembled. Students with high test scores may be less price sensitive, given their higher valuation of academic amenities of college [Jacob et al., 2018].

The outside option (non-enrollment, $j = 0$) is normalized to $V_{i0} = \varepsilon_{i0}$.

6.3.1 Uninformed Students

Uninformed students face the full posted price at every college. Their effective price is simply $\tilde{p}_{ijt} = p_{jt}$, so utility is:

$$V_{ij}^U = -\gamma_i \cdot p_{jt} + \phi \cdot d_{ij} + \sum_{\text{s(j)}\in\{\text{2y,4y,UM}\}} \alpha_{s(j)}^{SES} \cdot \mathbb{1}(s(j)=1) \cdot \text{HSpoverty}_i + \sum_{\text{s(j)}\in\{\text{2y,4y,UM}\}} \alpha_{s(j)}^{test} \cdot \mathbb{1}(s(j)=1) \cdot \text{Test}_i + \delta_{jt} + \varepsilon_{ij} \quad (6)$$

Choice probabilities follow standard logit:

$$P_{ij}^U = \frac{\exp(\bar{V}_{ij}^U)}{1+\sum_{k=1}^J \exp(\bar{V}_{ik}^U)}, \quad P_{i0}^U = \frac{1}{1+\sum_{k=1}^J \exp(\bar{V}_{ik}^U)} \quad (7)$$

where $\bar{V}_{ij}^U = V_{ij}^U - \varepsilon_{ij}$ is the deterministic component. Uninformed students never apply for TIP and have zero TIP receipt by construction. Students who are not eligible for TIP have the same choice problem as uninformed, eligible students.

6.3.2 Informed Students: Two-Stage Decision

Informed students face a richer decision problem with a two-stage sequential structure: first an application decision, then a college choice conditional on application status.

Stage 1: Application Decision. Informed students weigh the expected benefit of applying for TIP against the hassle cost. Define latent utilities:

$$V_i^{Apply} = B_i - \kappa_{it} + \epsilon_i^A, \qquad V_i^{NotApply} = \epsilon_i^N \quad (8)$$

where $\epsilon_i^A, \epsilon_i^N$ are i.i.d. Type 1 Extreme Value, B_i is the expected benefit (option value) of applying, and κ_{it} is the application cost. With these distributional assumptions, the application probability is logit:

$$\vartheta_i^A = \Pr(A_i = 1 \mid \tau_i = I) = \frac{\exp(B_i - \kappa_{it})}{1+\exp(B_i - \kappa_{it})} \quad (9)$$

Application costs reflect the bureaucratic steps required to access TIP, which we parameterize as a function of the aggregate aid application rate at students' high school:

$$\kappa_{it} = \kappa_{FAFSA} \cdot (1 - FAFSA_{h(i),t}) \quad (10)$$

The parameter κ_{FAFSA} captures the role of the school-level FAFSA completion environment: students at high schools where few peers complete the FAFSA face higher costs of navigating

the financial aid process.[7]

The application-cost equation reflects requirements documented by the qualitative work rather than a generic hassle-cost term. Counselors describe FAFSA completion as a major barrier because it requires parental cooperation, accurate financial information, trust in government, attention to deadlines, and correction of small errors. These costs are distinct from knowing about TIP: a student can know that TIP exists but still fail to complete the paperwork required for disbursement. School FAFSA completion rates proxy for the local capacity and culture around completing financial-aid paperwork.

The expected benefit B_i captures the option value of having TIP available when choosing among colleges. It equals the difference in inclusive values (expected maximum utilities) between the college choice problem with TIP and without:

$$B_i = \underbrace{\ln\left(1 + \sum_{k=1}^{J} \exp(\bar{V}_{ik}^{I,A})\right)}_{\text{Inclusive value with TIP application}} - \underbrace{\ln\left(1 + \sum_{k=1}^{J} \exp(\bar{V}_{ik}^{I,N})\right)}_{\text{Inclusive value without TIP application}} \tag{11}$$

This logsum difference is always non-negative: applying for TIP weakly expands the set of affordable options. Students with high B_i—those living near TIP-eligible colleges with high tuition, for instance—are more likely to apply.

Stage 2: College Choice. An informed student who applied for TIP incorporates the expected TIP award into the effective price at TIP-eligible colleges:

$$V_{ij}^{I,A} = \begin{cases} -\gamma_i \cdot (p_{jt} - q_{ijt} \cdot A_{jt}^{rule}) + \phi \cdot d_{ij} \\ + \sum_{\text{s(j)} \in \{\text{2y,4y,UM}\}} \alpha_{s(j)}^{SES} \cdot \mathbb{1}(s(j) = 1) \cdot \text{HSpoverty}_i \\ + \sum_{\text{s(j)} \in \{\text{2y,4y,UM}\}} \alpha_{s(j)}^{test} \cdot \mathbb{1}(s(j) = 1) \cdot \text{Test}_i + \delta_{jt} + \varepsilon_{ij} \quad \text{if } j \in \mathcal{J}^{TIP} \\ \\ -\gamma_i \cdot p_{jt} + \phi \cdot d_{ij} \\ + \sum_{\text{s(j)} \in \{\text{2y,4y,UM}\}} \alpha_{s(j)}^{SES} \cdot \mathbb{1}(s(j) = 1) \cdot \text{HSpoverty}_i \\ + \sum_{\text{s(j)} \in \{\text{2y,4y,UM}\}} \alpha_{s(j)}^{test} \cdot \mathbb{1}(s(j) = 1) \cdot \text{Test}_i + \delta_{jt} + \varepsilon_{ij} \quad \text{if } j \notin \mathcal{J}^{TIP} \end{cases} \tag{12}$$

where q_{ijt} is the probability of actually receiving TIP conditional on applying and enrolling (described below) and A_{jt}^{rule} is the deterministic TIP award. At TIP-eligible colleges, the effective price is reduced by the expected TIP transfer $q_{ijt} \cdot A_{jt}^{rule}$. At other colleges, TIP

[7] We normalize the baseline application cost κ_0 to zero, assuming no application cost for students at high schools at which every student completes a FAFSA. The intercept θ_0 in the type probability equation absorbs the overall level of the information-versus-cost tradeoff; see the identification discussion in Section 7.4. We also considered including a parameter to captures the cost imposed by the separate TIP application form, which was required prior to 2021 and subsequently eliminated. Unfortunately this parameter is not well-identified from the aggregate time trend.

has no effect.

An informed student who chose not to apply faces the full posted price everywhere, just like an uninformed student:

$$V_{ij}^{I,N} = -\gamma_i \cdot p_{jt} + \phi \cdot d_{ij} + \sum_{\text{s(j)}\in\{\text{2y,4y,UM}\}} \alpha_{s(j)}^{SES} \cdot \mathbb{1}(s(j)=1) \cdot \text{HSpoverty}_i + \sum_{\text{s(j)}\in\{\text{2y,4y,UM}\}} \alpha_{s(j)}^{test} \cdot \mathbb{1}(s(j)=1) \cdot \text{Test}_i + \delta_{jt} + \varepsilon_{ij} \quad (13)$$

Choice probabilities within each application state follow standard logit. The unconditional enrollment probability for an Informed student at college j integrates over the application decision:

$$P_{ij}^{I} = \vartheta_i^A \cdot P_{ij}^{I,A} + (1 - \vartheta_i^A) \cdot P_{ij}^{I,N} \quad (14)$$

6.4 Receipt Hazards

Not all TIP applicants who enroll at eligible colleges ultimately receive the scholarship. Receipt also depends on post-enrollment administrative steps—the college must verify high school graduation and enrollment status, confirm eligibility through inter-agency data systems, package TIP along with other aid correctly, and disburse funds—that can fail for reasons outside the student's control. We model these downstream barriers as a receipt hazard. Let h_{ijt} denote the hazard that the administrative process prevents student i from receiving TIP after applying and enrolling at college j. Successful receipt is then:

$$q_{ijt} = q_0 \cdot \exp(-h_{ijt}), \qquad q_0 \in (0, 1] \quad (15)$$

where the hazard is

$$h_{ijt} = \lambda_{Pell} \left(1 - \mathbf{1}\{Pell_i = 1\}\right) + \lambda_{adm} \left(1 - R_{j,t-1}^{TIP}\right). \quad (16)$$

This specification normalizes receipt to one when downstream barriers are absent (h_{ijt}=0). Pell recipients have already completed the FAFSA, clearing a major administrative prerequisite, so they avoid the non-Pell hazard λ_{Pell}. Colleges with higher lagged TIP take-up $R_{j,t-1}^{TIP}$ have a lower administrative hazard, captured by λ_{adm}, because prior take-up proxies for institutional familiarity with TIP, verification, billing and disbursement. Only informed students who applied and enrolled at a TIP-eligible college can receive TIP; all others have zero receipt probability.

The receipt hazard is motivated by evidence that non-receipt can occur after information and application decisions have been made. Financial-aid staff describe a fragmented process in which eligibility files, billing lists, FAFSA records, and institutional enrollment records

must line up. Colleges may also need to verify (sometimes manually) high-school graduation, residency, enrollment intensity, satisfactory academic progress, and program eligibility. Pell receipt is therefore used as a proxy for having cleared a key FAFSA prerequisite, while lagged college TIP take-up proxies for institutional experience and administrative capacity in processing TIP awards.

6.5 Summary of the Decision Structure

Figure 4 summarizes the timing and structure of the model. There are three distinct pathways by which a TIP-eligible student fails to receive the scholarship: (i) the student is Uninformed and never considers TIP; (ii) the student is Informed but hassle costs exceed the expected benefit of applying; or (iii) the student is Informed, applies, and enrolls at an eligible college, but administrative barriers prevent receipt. TIP receipt is therefore the joint outcome of awareness (π_i^I), application (ϑ_i^A), enrollment at a TIP-eligible college ($P_{ij}^{I,A}$), and successful receipt (q_{ijt}). This decomposition is central to our policy analysis: interventions that improve awareness (raising π_i^I), reduce hassle costs (lowering κ_{it}), or streamline administrative processing (raising q_{ijt}) target different margins and have different distributional consequences.

7 Estimation

7.1 Parameters

The structural parameters to be estimated are:

$$\psi = \Big\{ \underbrace{\gamma, \Gamma_{SES}, \Gamma_{test}, \{\alpha_s^{SES}, \alpha_s^{test}\}_{\text{s}\in\{\text{2y,4y,UM}\}}, \phi}_{\text{preferences}}, \underbrace{\theta_0, \theta_m, \theta_X}_{\text{type probability}} , \underbrace{\kappa_{FAFSA}}_{\text{application costs}} , \underbrace{q_0, \lambda_{Pell}, \lambda_{adm}}_{\text{receipt hazard}} \Big\} \tag{17}$$

a total of 17 parameters governing preferences, information, application costs, and post-enrollment receipt hazards. In addition, the model includes college-by-cohort mean utilities $\{\delta_{jt}\}_{j,t}$, which are high-dimensional parameters recovered in an inner loop.

7.2 Likelihood

We observe three types of outcomes for each eligible student: enrollment with TIP receipt, enrollment without receipt, and non-enrollment. The likelihood contribution depends on which outcome is realized.

Enrollee with TIP receipt ($y_{ij} = 1$, $R_i = 1$). Receiving TIP reveals that the student must have been Informed, applied, chosen college j, and successfully complied:

$$\mathcal{L}_i = \pi_i^I \cdot \vartheta_i^A \cdot P_{ij}^{I,A} \cdot q_{ijt} \tag{18}$$

Enrollee without TIP receipt ($y_{ij} = 1$, $R_i = 0$). The student enrolled at college j but did not receive TIP. This is consistent with three latent paths:

$$\mathcal{L}_i = \underbrace{\pi_i^I \cdot \vartheta_i^A \cdot P_{ij}^{I,A} \cdot (1 - q_{ijt})}_{\text{Informed, applied, receipt failed}} + \underbrace{\pi_i^I \cdot (1 - \vartheta_i^A) \cdot P_{ij}^{I,N}}_{\text{Informed, did not apply}} + \underbrace{(1 - \pi_i^I) \cdot P_{ij}^U}_{\text{Uninformed}} \tag{19}$$

Non-enrollee ($y_{i0} = 1$). The student chose the outside option:

$$\mathcal{L}_i = \pi_i^I \cdot \left[\vartheta_i^A \cdot P_{i0}^{I,A} + (1 - \vartheta_i^A) \cdot P_{i0}^{I,N}\right] + (1 - \pi_i^I) \cdot P_{i0}^U \tag{20}$$

Non-eligible students contribute only via their enrollment decisions. All choice probabilities are closed-form logit expressions, so no simulation draws are required. The log-likelihood is $\ell(\psi) = \sum_{i=1}^N \log \mathcal{L}_i$.

7.3 Estimation

We estimate the model using a nested fixed-point (NFXP) GMM procedure. For any candidate parameter vector ψ, the inner loop recovers the college-by-cohort mean utilities $\{\delta_{jt}\}$ that match observed enrollment shares. Specifically, predicted shares are computed from the model's choice probabilities, integrating over information and application states, and δ_{jt} is updated until model-predicted college-year shares equal the observed shares.

The outer loop chooses ψ to minimize a GMM objective that stacks likelihood score moments with auxiliary reduced-form moments. Let

$$g_i(\psi) = \begin{pmatrix} s_i(\psi) \\ h_i(\psi) \\ a_i(\psi) \end{pmatrix} \in \mathbb{R}^{24}, \qquad \bar{g}_N(\psi) = \frac{1}{N} \sum_{i=1}^N g_i(\psi). \tag{21}$$

The estimator solves

$$\hat{\psi} = \arg\min_{\psi} \; N \bar{g}_N(\psi)' W_N \bar{g}_N(\psi). \tag{22}$$

The first block, $s_i(\psi) \in \mathbb{R}^{17}$, contains the individual likelihood score contributions for the free structural parameters. Averaging these scores embeds the likelihood first-order conditions in the GMM objective. The second block, $h_i(\psi) \in \mathbb{R}^2$, contains the two auxiliary matching moments: the model analogs of the reduced-form coefficients $(\hat{\beta}_0, \hat{\beta}_1)$ on TIP eligibility and TIP eligibility interacted with Medicaid months beyond 24. These are computed using model-predicted enrollment probabilities, restricting to students with 24–96 total Medicaid months and applying the same matching specification as in Table 5. The resulting moments are $\beta_0(\psi) - \hat{\beta}_0$ and $\beta_1(\psi) - \hat{\beta}_1$.

The third block, $a_i(\psi) \in \mathbb{R}^5$, targets receipt/compliance moments among TIP-eligible students enrolled at TIP colleges. These compare model-predicted and observed TIP receipt

rates overall, separately by Pell status, and separately by whether the enrolled college has low or high lagged TIP take-up. These moments discipline the baseline receipt probability and heterogeneity in receipt by Pell status and administrative environment.

We use two-step GMM. The first step sets $W_N = I$. At the first-step estimates, we estimate the covariance matrix of the stacked moments, $\hat{\Omega}$, and use $W_N = \hat{\Omega}^{-1}$ in the second step. Standard errors are computed using the usual GMM sandwich formula based on the numerical Jacobian of $\bar{g}_N(\psi)$ with respect to the free parameters.

7.3.1 Estimation Sample

The administrative data contain 997,545 Michigan public high school graduates from 2011 to 2021, including 337,553 TIP-eligible students and 659,992 ineligible students across 77 colleges, 1,345 high schools, and 18 commuting zones.[8] Students are given a choice set that includes all colleges (regardless of sector) located within their commuting zone, all public four-year colleges in the state, a generic out-of-state enrollment option, and non-enrollment outside option. The estimates reported below use a 50% random subsample of these linked microdata. Ineligible students help identify baseline demand—price sensitivity, distance preferences, and college-by-cohort mean utilities—because their enrollment choices are not directly affected by TIP.

7.4 Identification

The model has four groups of parameters: preferences, information, application costs, and receipt hazards. We identify them from distinct patterns in the microdata. Enrollment choices reveal how students trade off price, distance, and college quality. TIP receipt reveals the joint probability that a student is informed, applies, enrolls at a TIP-eligible college, and successfully receives the award. The auxiliary moments summarize several additional patterns that are central for separating the latent channels: the Medicaid gradient in the enrollment effect of TIP eligibility and the overall level of compliance. The identifying content of the model is that different parameters move different empirical gradients.

Preference parameters. The college-by-cohort mean utilities δ_{jt} absorb demand factors that are common to all students considering college j in cohort t, including any college-time variation in posted prices that is not student-specific. The price coefficient γ is therefore identified from variation in the effective price faced by different students for the same college in the same cohort, especially in-district versus out-of-district tuition differences. Most colleges in our setting are public institutions whose tuition is set through system-wide budgeting and political processes rather than institution-specific demand shocks. The

[8] This sample is smaller than that shown in Table 1 as it excludes students that attend colleges outside of their choice set.

heterogeneous components Γ_{SES} and Γ_{test} are identified from differential responses to this student-specific price variation across students with varying levels of economic disadvantage and test scores. The distance parameter ϕ is identified from the systematic tendency of students to enroll at nearby colleges, conditional on college-by-cohort mean utility and price. Finally, $\{\alpha_s^{SES}, \alpha_s^{test}\}_{\text{s}\in\{\text{2y,4y,UM}\}}$ are identified by differences in enrollment patterns by SES and achievement.

Type probability. The parameters $(\theta_0, \theta_m, \theta_X)$ are identified from variation in TIP receipt rates across students with different Medicaid histories and school characteristics. Observing TIP receipt ($R_i = 1$) reveals that the student was Informed and applied, so cross-sectional variation in receipt rates by (m_i, X_{ht}) traces out the type probability function. Crucially, Medicaid months m_i are excluded from the cost and receipt-hazard equations, so the gradient of receipt rates with respect to m_i identifies θ_m separately from cost and downstream receipt effects. This exclusion is motivated by the companion evidence: Medicaid duration primarily shifts safety-net embeddedness and visibility to counselors, while concrete application and receipt barriers are tied to FAFSA completion, the separate TIP form, and institutional processing. School-level characteristics X_{ht}, such as the counselor-to-pupil ratio, are similarly excluded from other channels because they proxy for the local information environment.

Application costs. The FAFSA coefficient κ_{FAFSA} is identified from cross-school variation in TIP take-up that correlates with school-level FAFSA completion rates, conditional on the type probability shifters. The interpretation of FAFSA rates as application-cost shifters is supported by counselor interviews that frame FAFSA as paperwork, parental-consent, documentation, and deadline burden rather than as a source of TIP eligibility information.

Receipt hazards. The parameters $(\lambda_{Pell}, \lambda_{adm})$ are identified from variation in receipt conditional on enrollment at TIP-eligible colleges. Pell Grant receipt enters only the receipt hazard, so λ_{Pell} is identified from within-college-year differences in receipt rates between Pell and non-Pell students. This placement reflects the institutional role of Pell as evidence that the student has navigated FAFSA and financial aid processes at the college, not as evidence that the student knew about TIP. Lagged college-level take-up identifies λ_{adm} from cross-college variation in receipt conditional on application; the receipt-hazard interpretation is grounded in financial-aid staff accounts of college-level variation in roster reconciliation, manual verification, packaging rules, and state-aid experience. The exponential form constrains these hazards to reduce receipt probabilities, which aligns the parameter signs with the institutional interpretation.

Mean utilities. The college-by-cohort mean utilities $\{\delta_{jt}\}$ are recovered through the BLP contraction mapping. For given structural parameters, they adjust to rationalize observed enrollment shares at each college-year cell, absorbing demand variation not captured by price, distance, SES, and test scores.

7.5 Estimates

Table 7 reports estimates.[9]

Preferences. The estimated price coefficient is $\hat{\gamma} = 0.149$ (SE = 0.004), implying that a \$1,000 reduction in annual tuition increases the mean utility index by approximately 0.15. The heterogeneity parameter $\hat{\Gamma}_{SES} = 0.025$ (SE = 0.002) indicates that students who were on FRPL in high school are roughly 16% more price-sensitive than those who were not ($\gamma_i = 0.174$ versus 0.149), consistent with the intuition that the marginal utility of a tuition dollar is higher for students with fewer financial resources. Conversely, students with higher test scores are less price sensitive. The distance coefficient $\hat{\phi} = -0.0153$ (SE = 0.0002) confirms that students prefer nearby colleges. The utility shifters $\{\alpha_s^{SES}, \alpha_s^{test}\}_{\text{s}\in\{\text{2y,4y,UM}\}}$ all go in the expected direction, with low income students less likely to enroll anywhere, but particularly at U Michigan - Ann Arbor. High acheiving students have the opposite patterns, being more likely to enroll at four-year colleges and particularly at U Michigan - Ann Arbor. All preference parameters are precisely estimated.

Information. The type probability parameters $\hat{\theta}_0 = -4.355$ and $\hat{\theta}_m = 0.118$ together imply that the share of informed students rises sharply with safety-net exposure. Among students near the eligibility threshold ($m \in [24, 26]$), the model implies an informed share of approximately 48%. The average informed share among eligible students is much higher, about 96%, because many eligible students have substantially longer Medicaid histories. The school-level coefficient $\hat{\theta}_X = 0.402$ is positive, suggesting that school-level guidance environments also shape awareness. These estimates provide a structural explanation for the reduced-form puzzle: the null RD effect arises because barely-eligible students are mostly uninformed, so eligibility has little effect on their behavior. The positive matching estimates reflect the higher informed share among students with greater Medicaid exposure.

Application costs. The FAFSA coefficient is substantial ($\hat{\kappa}_{FAFSA} = 0.312$, SE = 0.115), indicating that students at schools with low FAFSA completion rates face a meaningful barrier to TIP application.

[9] We estimate on a 50% random subsample ($N = 499$) with 24 moment conditions (17 score + 2 matching + 5 compliance/receipt rate). Standard errors are from the GMM sandwich formula.

Receipt hazards. The receipt equation is parameterized as a hazard, so larger values of λ_{Pell} and λ_{adm} lower the probability of successful receipt. The estimated non-Pell hazard is $\hat{\lambda}_{Pell} = 0.106$, implying that non-Pell students face a substantially higher risk of failing to receive TIP after applying and enrolling. This is consistent with the institutional reality that Pell recipients have already completed the FAFSA and received other forms of aid. The administrative hazard is $\hat{\lambda}_{adm} = 0.740$, indicating meaningful cross-college variation in receipt: applicants at colleges with low lagged TIP take-up are less likely to receive the award. Across enrolled TIP-college students, the mean predicted receipt probability is approximately 57%.

7.6 Model Fit

The model fits the moments most central to the decomposition of TIP non-receipt. Table 8 summarizes the targeted moments (bolded), latent model implications, and several non-targeted moments. The choice-specific shifters mean that we match the overall and sector-specific enrollment rates exactly. However, we also match the enrollment and TIP-receipt patterns of TIP-eligible students very well, though these are not targeted. The Medicaid gradient in the matching design is reasonably matched: the model-implied slope is 0.0007, compared with an empirical target of 0.00155. The pooled school-level application rate is also matched closely, with a model prediction of 0.5058 relative to 0.522 in the observed application-rate cohorts. These two moments discipline the latent margins that matter most for the counterfactuals: the Medicaid gradient pins down how information rises with safety-net exposure, while the application-rate moment anchors the level of application behavior among students who know about TIP.

Figure 5 depicts the TIP receipt rate (overall and conditional) and enrollment rate separately by total months on Medicaid, both in the actual data and implied by the model. Our model captures the broad features of take-up increasing sharply with Medicaid exposure while college enrollment declines. Our model under-predicts the gradient in all three outcomes for students with more than 10 years of Medicaid participation. Figure 6 reports TIP treatment effects (on TIP receipt and enrollment) by blocks of Medicaid months implied by our model and compares these to the estimated treatment effects from our matching approach (Table 5, all Panels). We capture the gradient in TIP treatment effects, though underpredict enrollment effects at 42-47 months and overpredict TIP receipt effects throughout. Finally, Figure 7 reports TIP receipt model fit, separately for several student characteristics, including HS FAFSA completion rate (Panel A), Pell grant recipient (Panel B), and lagged college-level compliance (Panel C). The model generally captures the qualitative patterns emphasized by the institutional evidence: receipt is higher for Pell students and rises with lagged college TIP take-up, though the relationships are attenuated

The estimated information process rationalizes the contrast between the RD and

matching estimates that motivates the structural exercise. Figure 8 reports the implied share of eligible students that are informed about TIP as a function of Medicaid months. Near the eligibility threshold, the estimated informed share is low: among students with 24–26 Medicaid months, $\hat{\pi}^I$ is approximately 0.48. At higher Medicaid exposure, the informed share rises sharply, plateauing after about 6 years (72 months). Among all eligible students, the rate is about 0.96.

The main limitation is that the model underpredicts TIP receipt and overpredicts enrollment for eligible students with a high level of Medicaid exposure, possibly since these relationships are extrapolated from individuals with less exposure. We also underpredict the TIP receipt gain associated with Pell. Finally, our model predicts a TIP enrollment effect for marginal students that is equal to that from our matching estimator, but exceeds that from our RD approach since these two differ. To the extent that the matching estimate overstates the true causal effect of TIP, our overall TIP effects may overstate the causal effect. The role of various frictions in mediating these effects, however, are not obviously subject to the same bias. Nonetheless, the model reproduces the key patterns needed for the policy analysis: low information near the threshold, rising awareness with safety-net exposure, meaningful FAFSA-related application costs, and persistent receipt hazards after enrollment.

8 Counterfactual Simulations

We use the estimated model to evaluate how different frictions mediate predicted effects of financial aid. We begin from the baseline scenario, in which all estimated frictions are present, then sequentially remove information frictions, application frictions, and receipt or compliance frictions.[10] At each step we simulate the effect of TIP eligibility by comparing scenarios with and without TIP. The No TIP benchmark is actually the same under each counterfactual friction scenario since the frictions we model only matter in the presence of financial aid. The full information scenario (D1) sets $\pi_i^I = 1$ for all students. The no application cost scenario (D2) sets $\vartheta_i^A = 1$ for all informed students, similar to what we might see from requiring FAFSA application for high school graduation. This scenario likely provides an upper bound of the impact of application cost reduction. We thus also simulate a scenario that sets $\kappa_{it} = 0$ for all Informed students, thus closing the gap between high and low FAFSA high schools, but not reducing application costs beyond that. Finally, the perfect compliance scenario (D3) increases q_{ijt} by 0.25 points at all TIP-participating 2-year colleges (up to a max of 1).[11]

Panel A of Table 9 reports the sequential decomposition for all TIP-eligible students

[10] We've reversed the order of the decomposition and the qualitative patterns are similar.

[11] In [Thompson et al., 2025] we found that for a student with all favorable factors (many years on Medicaid, high FAFSA high school, on Pell, enrolled at a TIP-eligible college with high take-up), TIP take-up topped out at around 75%. We interpret the remaining 25% as due to compliance failures.

in the estimation sample. In the baseline, 31.6% of eligible students enroll in community college and 61.6% enroll in any college. Moving to full information raises both community college and overall enrollment by 0.11 percentage points. Removing application frictions on top of full information adds 3.50 percentage points for community college enrollment and 3.46 percentage points for total enrollment. Eliminating receipt hazards then adds 4.16 percentage points for community college enrollment and 2.47 percentage points for total enrollment. Panel B expresses these same scenarios as TIP treatment effects relative to the no-TIP counterfactual: the baseline TIP effect is 3.49 (3.65) percentage points for community college (overall) enrollment. [12] Removing all frictions increases the effect of TIP considerably: a 9.7 percentage point increase in enrollment overall and 11.26 percentage points at community colleges. The presence of these three frictions thus dampens the effectiveness of TIP considerably. Gains are particularly due to the removal of application costs (57% of the 6 percentage point increase in TIP effect) and non-compliance (41%), with relatively little role from improved information (2%).

The decomposition differs sharply by where students sit in the Medicaid distribution. Table 10 repeats the same sequential exercise for students near the eligibility threshold ($m \in [24, 35]$). For this group, the baseline enrollment effect of TIP is much smaller: 1.74 percentage point overall and 1.86 at community college specifically, as seen in the reduced-form analysis. The cost of all frictions is also significant for this group: a frictionless TIP program would raise community college enrollment by 10.10 percentage points and total enrollment by 7.75 percentage points relative to the baseline. Information frictions are also much more important for students near the threshold, accounting for 21% of the 6 percentage point treatment effect gain overall. Application costs are still also important (46%) as is non-compliance (34%). This is exactly the population for which the RD finds small effects of eligibility, and the counterfactuals suggest why: many of these students do not know enough about TIP for the program to shape their college choice.

Figure 9 shows these patterns graphically. For students in 6-month Medicaid bins, we report the simulated baseline TIP enrollment effect, overall and at community colleges, as well as the incremental effect when each friction is removed. Information frictions are largest at the eligibility threshold of 24 months, undercutting the effectiveness of TIP aid by nearly 2 percentage points. Information frictions play no role beyond 60 months (5 years) of Medicaid participation. Presumably, students with this level of attachment to the social safety net have had enough opportunity to learn about TIP. Application and non-compliance frictions are comparatively flat across the distribution, lowering overall and community college enrollment by roughly 2–4 percentage points in every bin. Figure 10 reports a similar decomposition for a counterfactual with a small reduction in application

[12] These are slightly larger than the average TIP effects reported in 4, reflecting that the matching sample excludes students with more than 8 years of Medicaid participation.

costs, operationalized by equalizing application costs between high and low FAFSA filing high schools. The role of applicaiton costs is considerably reduced, but the patterns related information and compliance are unaffected.

These results clarify the policy content of the model. Information frictions explain why the RD effect is small near the eligibility threshold, but they are not the only barrier limiting TIP's overall effect. For the full eligible population, the largest gains come from reducing application frictions and receipt hazards. A policy package that combines better outreach with FAFSA assistance and more reliable post-enrollment disbursement would therefore have substantially larger effects than any single intervention.

9 Conclusion

Michigan's Tuition Incentive Program (TIP) has many desirable features: it is first-dollar, eligibility is tied to safety net participation, continuation is guaranteed, and students are potentially informed early enough to alter their college plans. Despite this, take-up among eligible students is low and effects of the program are heterogeneous. TIP eligibility has no effect on enrollment among students near the eligibility threshold but larger effects further from the threshold. We reconcile these patterns by hypothesizing that students near the threshold are likely to be the least informed about the program and their eligibility for it. Information and other frictions may thus mediate the effects of aid eligibility on enrollment, a lesson that prior work has also emphasized based on comparisons across programs [Dynarski et al., 2022].

We develop a structural model of aid awareness, application, college choice, and aid receipt to assess whether reducing information frictions, application costs, and administrative hurdles could improve TIP's impact on enrollment. A key feature of the model is the inclusion of heterogeneity in information about TIP, the costs of applying for it, and the difficulty of completing the take-up process. We estimate the model by combining maximum likelihood estimation with auxiliary reduced-form moments from the first half of the paper in a GMM framework, along with a contraction mapping to account for mean utility differences for each college.

Counterfactual simulations show that frictions have economically meaningful consequences. Under the estimated baseline, TIP raises community college enrollment by 3.49 percentage points and total enrollment by 3.65 percentage points relative to a no-TIP counterfactual. With all frictions removed, these effects rise to 11.26 and 9.70 percentage points, respectively. Information frictions are most important near the eligibility threshold, while application frictions and receipt hazards account for low treatment effects in the broader eligible population. These results suggest that outreach, FAFSA support, and reliable post-enrollment disbursement are complements rather than substitutes.

The State of Michigan has made significant changes which may improve TIP take-up recently, including removing the requirement for a separate TIP application, increasing student outreach, and implementing a new universal scholarship that may "crowd-in" use of TIP. A large increase in TIP volume in 2023-2024 relative to the prior year suggests some of these efforts may be paying off. Our analysis focuses on a time period when many of these administrative barriers still existed.

Finally, it is likely that additional aid may reduce other financial burdens students face when attending college even if it does not alter their educational attainment, improving overall economic well-being. For instance, additional aid may reduce debt burden or relieve students from working less during school, which has been shown to be beneficial. Examining these outcomes is a useful direction for future work.

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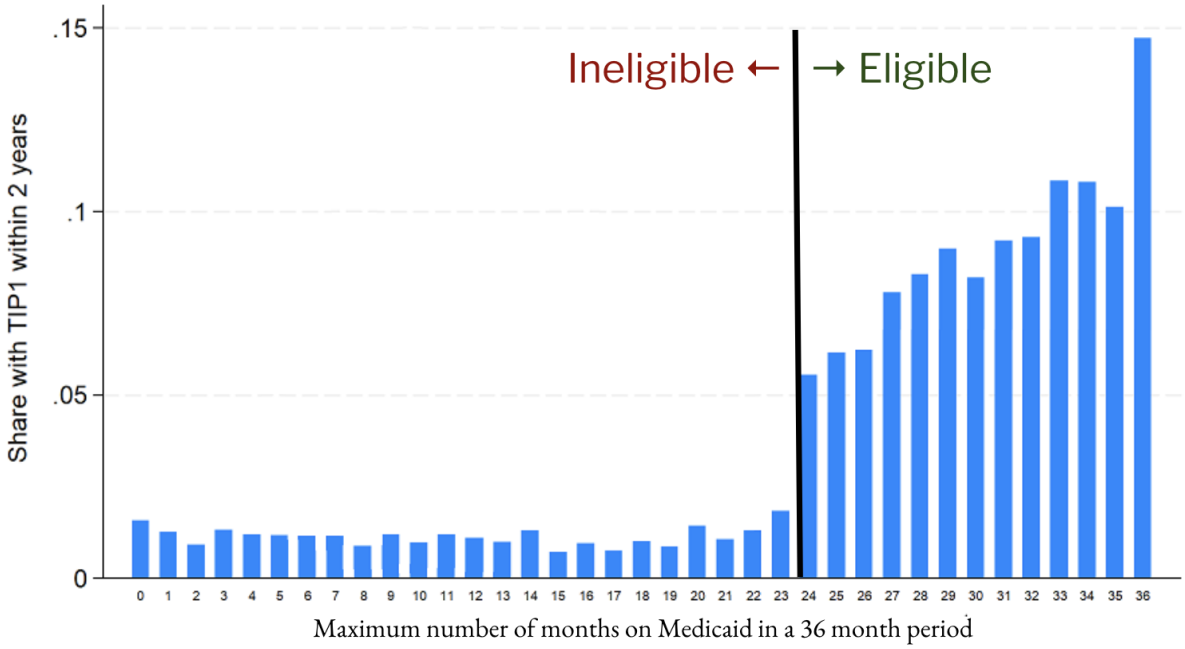
Tables and Figures

Table 1: Summary Statistics

		Months on Medicaid in 36mo window		Months on Medicaid in 36mo window	
	All students	< 24 (Not Elig)	24 to 36 (Elig)	22-23 (Not Elig)	24-25 (Elig)
Number of observations	1,179,599	778,008	401,591	8,065	13,103
Baseline characteristics					
Female	0.507	0.504	0.514	0.516	0.499
White	0.770	0.829	0.657	0.742	0.745
Black	0.167	0.113	0.273	0.185	0.182
Hispanic	0.057	0.042	0.086	0.071	0.074
Asian-American	0.039	0.044	0.029	0.038	0.036
American Indian or Alaskan Native	0.017	0.014	0.022	0.023	0.022
Native Hawaiian or Other Pacific Islander	0.003	0.003	0.002	0.002	0.002
Two or more races	0.017	0.015	0.021	0.021	0.020
SAT score	998	1041	925	963	967
ACT score	20	21	18	19	19
Receives special education services?	0.085	0.068	0.117	0.089	0.086
Fraction of K12 Observations with FRPL	0.376	0.203	0.711	0.492	0.505
Total Months on Medicaid*	46.2	4.7	126.5	50.3	53.7
Total Months on TANF*	5.1	0.3	14.5	2.9	2.7
Total Months on SNAP*	27.9	2.3	77.4	24.2	25.9
Enrollment					
Enrolled in any college	0.728	0.782	0.622	0.662	0.661
Enrolled in public 2-year college	0.389	0.395	0.377	0.383	0.381
Financial aid					
Receive TIP Phase I	0.057	0.015	0.139	0.015	0.056
Total Amount of TIP Phase I Received	283.16	72.83	696.50	59.78	304.02
Received MTG	0.028	0.029	0.025	0.023	0.029
Total Amount of MTG Received	74.61	77.39	69.14	60.75	80.05
Received MCS	0.074	0.084	0.056	0.069	0.072
Total Amount of MCS Received	98.02	110.49	73.52	86.65	96.79
Total Amount of State Aid Received	470.47	272.98	858.58	221.04	498.64

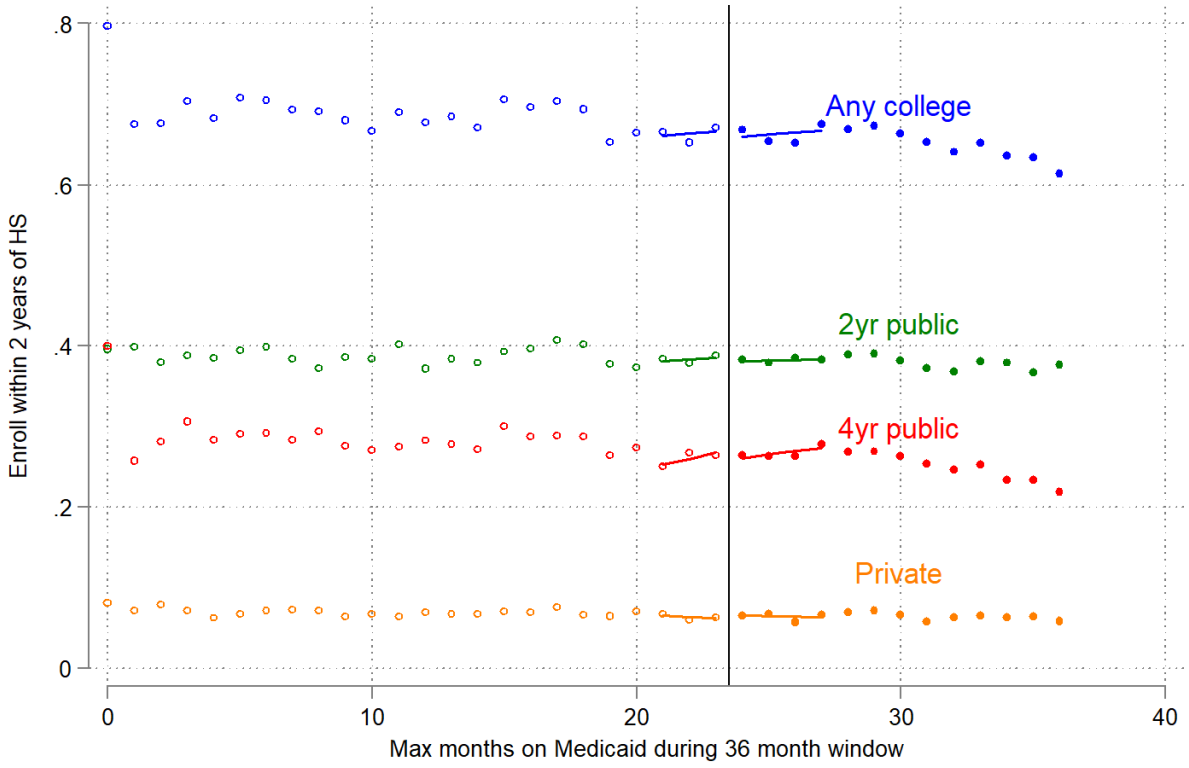
Notes: Sample includes all Michigan high school graduates from 2011 to 2021. *Months are measured over K12 records; Enrollment and financial aid is measured within two years of HS graduation.

Figure 1: RD: Effect of Eligibility on TIP Receipt



Notes: Figure reports the share of students that receive TIP Phase I within two years of high school graduation separately by the maximum number of months on Medicaid across all 36 month windows between age 9 and high school graduation. Individuals must have at least 24 months to be eligible for TIP. Sample includes all Michigan high school graduates from 2011 to 2021.

Figure 2: RD: Effect of Eligibility on Enrollment



Notes: Figure plots the average enrollment rate overall and by sector, separately by the maximum number of Medicaid months in all 36 month periods since age 9. Individuals with at least 24 months are eligible for TIP. Lines fitted to the three observations on each side of the threshold (weighted by number of students) are also shown.

Table 2: RD: Effect of TIP Eligibility on Financial Aid

	Within 1yrs	Within 2yrs	Within 3yrs	Within 4yrs	Within 5yrs	Within 6yrs
A. Receive TIP Phase I						
Estimate	0.029	0.035	0.037	0.034	0.035	0.037
Std. Error	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)
P-Value	0.000	0.000	0.000	0.000	0.000	0.000
Optimal Bandwidth	[21, 27]	[21, 27]	[21, 27]	[21, 27]	[21, 27]	[21, 27]
N	37,448	34,528	31,333	28,185	24,850	21,530
B. Total Amount of TIP Phase I Received						
Estimate	122.398	221.093	282.654	265.627	259.608	260.984
Std. Error	(15.689)	(26.659)	(36.001)	(42.209)	(46.093)	(53.438)
P-Value	0.000	0.000	0.000	0.000	0.000	0.000
Optimal Bandwidth	[21, 27]	[21, 27]	[21, 27]	[21, 27]	[21, 27]	[21, 27]
N	37,448	34,528	31,333	28,185	24,850	21,530
C. Received Pell Grant						
Estimate	−0.021	−0.020	−0.015	−0.035	−0.023	−0.024
Std. Error	(0.014)	(0.016)	(0.015)	(0.018)	(0.015)	(0.019)
P-Value	0.134	0.211	0.317	0.052	0.125	0.207
Optimal Bandwidth	[21, 27]	[21, 27]	[21, 27]	[21, 27]	[21, 27]	[21, 27]
N	37,448	34,528	31,333	28,185	24,850	21,530
D. Total Amount of State Aid Received						
Estimate	136.174	248.050	338.477	365.474	406.078	387.546
Std. Error	(18.840)	(33.259)	(47.448)	(59.518)	(68.856)	(77.107)
P-Value	0.000	0.000	0.000	0.000	0.000	0.000
Optimal Bandwidth	[21, 27]	[21, 27]	[21, 27]	[21, 27]	[21, 27]	[21, 27]
N	37,448	34,528	31,333	28,185	24,850	21,530

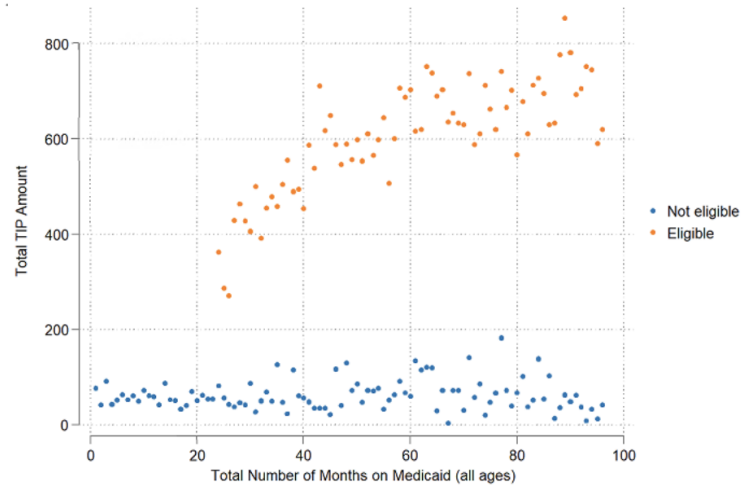
Notes: RD coefficients are from local linear regressions with optimal bandwidths per Calonico, Cattaneo, and Titiunik (2014, 2015). Standard errors are robust. Means and samples correspond to the optimal RD bandwidth for each horizon.

Table 3: RD: Effect of TIP Eligibility on Enrollment

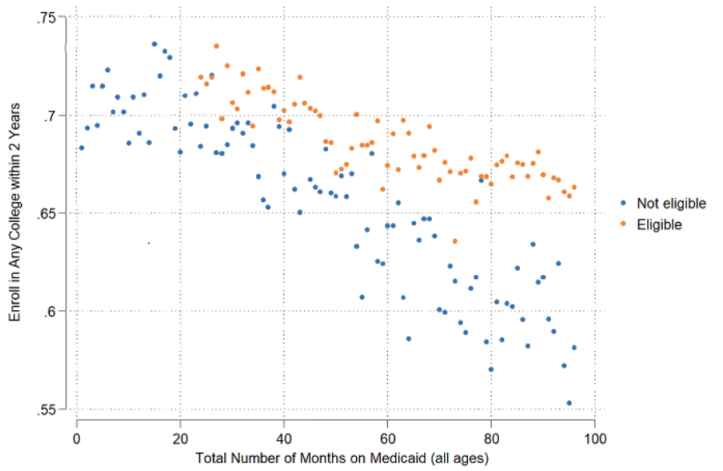
	Within 1yrs	Within 2yrs	Within 3yrs	Within 4yrs	Within 5yrs	Within 6yrs
A. Enroll in Any College Within 2 Years						
Estimate	−0.015	−0.015	−0.008	−0.016	−0.021	−0.017
Std. Error	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.017)
P-Value	0.317	0.317	0.594	0.317	0.189	0.317
Optimal Bandwidth	[21, 27]	[21, 27]	[21, 27]	[21, 27]	[21, 27]	[21, 27]
N	37,448	34,528	31,333	28,185	24,850	21,530
B. Enroll in Public 2-year College Within 2 Years						
Estimate	−0.008	−0.016	−0.008	−0.012	−0.008	−0.001
Std. Error	(0.017)	(0.019)	(0.020)	(0.020)	(0.018)	(0.018)
P-Value	0.638	0.400	0.689	0.549	0.657	0.956
Optimal Bandwidth	[22, 26]	[22, 26]	[22, 26]	[21, 27]	[21, 27]	[21, 27]
N	26,401	24,336	22,034	28,185	24,850	21,530
C. Enroll in Public 4-year College Within 2 Years						
Estimate	−0.002	0.000	0.002	−0.001	−0.006	−0.007
Std. Error	(0.013)	(0.016)	(0.015)	(0.018)	(0.019)	(0.023)
P-Value	0.878	1.000	0.894	0.956	0.752	0.761
Optimal Bandwidth	[21, 27]	[21, 27]	[21, 27]	[21, 27]	[21, 27]	[22, 26]
N	37,448	34,528	31,333	28,185	24,850	15,122

Notes: RD coefficients are from local linear regressions with optimal bandwidths per Calonico, Cattaneo, and Titiunik (2014, 2015). Standard errors are robust. Means and samples correspond to the optimal RD bandwidth for each horizon.

Figure 3: Matching: Effect of Eligibility on TIP Receipt and Enrollment



(a) Total TIP Amount



(b) Enrollment

Notes: Figure shows the average TIP amount (Panel A) and college enrollment rate within two years (Panel B) separately for cells defined by the number of total months on Medicaid from birth until high school graduation and by TIP eligibility. Individuals must have at least 24 months within any 36 month window between age 9 and high school graduation to be eligible for TIP. Sample includes all Michigan high school graduates from 2011 to 2021. Individuals with more than 96 months (8 years) are excluded as almost all are TIP-eligible.

Table 4: Matching on Observables Regression Estimates

Outcome	(1)	(2)	(3)	(4)	(5)	(6)
Received TIP	0.105***	0.0953***	0.0669***	0.0678***	0.0669***	0.0624***
(Control mean = .0136)	(0.00113)	(0.00118)	(0.00165)	(0.00165)	(0.00166)	(0.00171)
TIP amount received	563.6***	517.7***	360.7***	361.3***	359.9***	337.5***
(Control mean = 61.98)	(8.290)	(8.714)	(12.30)	(12.33)	(12.37)	(12.76)
Attend any college	0.0121***	0.0237***	0.0405***	0.0359***	0.0318***	0.0258***
(Control mean = .660)	(0.00277)	(0.00288)	(0.00513)	(0.00472)	(0.00474)	(0.00478)
Attend in-district CC	0.00929***	0.0123***	0.0141***	0.0138***	0.0118***	0.0084***
(Control mean = .146)	(0.00211)	(0.00218)	(0.00389)	(0.00388)	(0.00390)	(0.00394)
Attend public 2-year college	0.0183***	0.0223***	0.0280***	0.0276***	0.0255***	0.0205***
(Control mean = .374)	(0.00286)	(0.00297)	(0.00529)	(0.00526)	(0.00528)	(0.00534)
Attend public 4-year college	-0.00278	0.00681**	0.0193***	0.0128***	0.0109**	0.0083**
(Control mean = .267)	(0.00261)	(0.00271)	(0.00480)	(0.00430)	(0.00433)	(0.00437)
Observations	163,759	163,759	163,759	163,759	163,759	160,777
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Total Medicaid Month Dummies	No	Yes	No	No	Yes	Yes
Age 9+ Medicaid Month Dummies	No	No	Yes	Yes	Yes	Yes
Medicaid Spell Dummies	No	No	No	No	No	Yes
Other Controls	No	No	No	Yes	Yes	Yes

Notes: All models are restricted to students with 24 to 96 total months of Medicaid. Robust standard errors in parentheses. All outcomes are measured within 2 years of HS graduation.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 5: Matching Effects: Heterogeneity

	(1) Received TIP	(2) TIP Amount received	(3) Attend any college	(4) Attend in-district CC	(5) Attend public 2-year college	(6) Attend public 4-year college
A. All (N = 160,777)						
TIP Eligible	0.0409***	234.5***	0.0133*	0.00348	0.00661	0.00263
	(0.00257)	(19.30)	(0.00751)	(0.00619)	(0.00832)	(0.00685)
TIP Eligible × Months on Medicaid Beyond 24	0.00268***	12.83***	0.00155**	0.000607	0.00173**	0.000703
	(0.000220)	(1.653)	(0.000736)	(0.000588)	(0.000789)	(0.000638)
B. Months on Medicaid: 24 to 29 (N = 23,655)						
TIP Eligible	0.0484***	286.6***	0.0183**	0.000274	0.0119	0.00857
	(0.00263)	(20.18)	(0.00728)	(0.00609)	(0.00813)	(0.00674)
C. Months on Medicaid: 30 to 35 (N = 18,219)						
TIP Eligible	0.0665***	348.9***	0.0262***	0.0168**	0.0214**	0.00730
	(0.00314)	(24.38)	(0.00812)	(0.00660)	(0.00908)	(0.00743)
D. Months on Medicaid: 36 to 41 (N = 19,293)						
TIP Eligible	0.0742***	428.5***	0.0324***	0.00969	0.0193	0.0154
	(0.00404)	(29.01)	(0.0112)	(0.00901)	(0.0123)	(0.00995)
E. Months on Medicaid: 42 to 47 (N = 16,817)						
TIP Eligible	0.0944***	529.7***	0.0556***	0.0126	0.0627***	0.00191
	(0.00499)	(32.64)	(0.0182)	(0.0140)	(0.0189)	(0.0155)

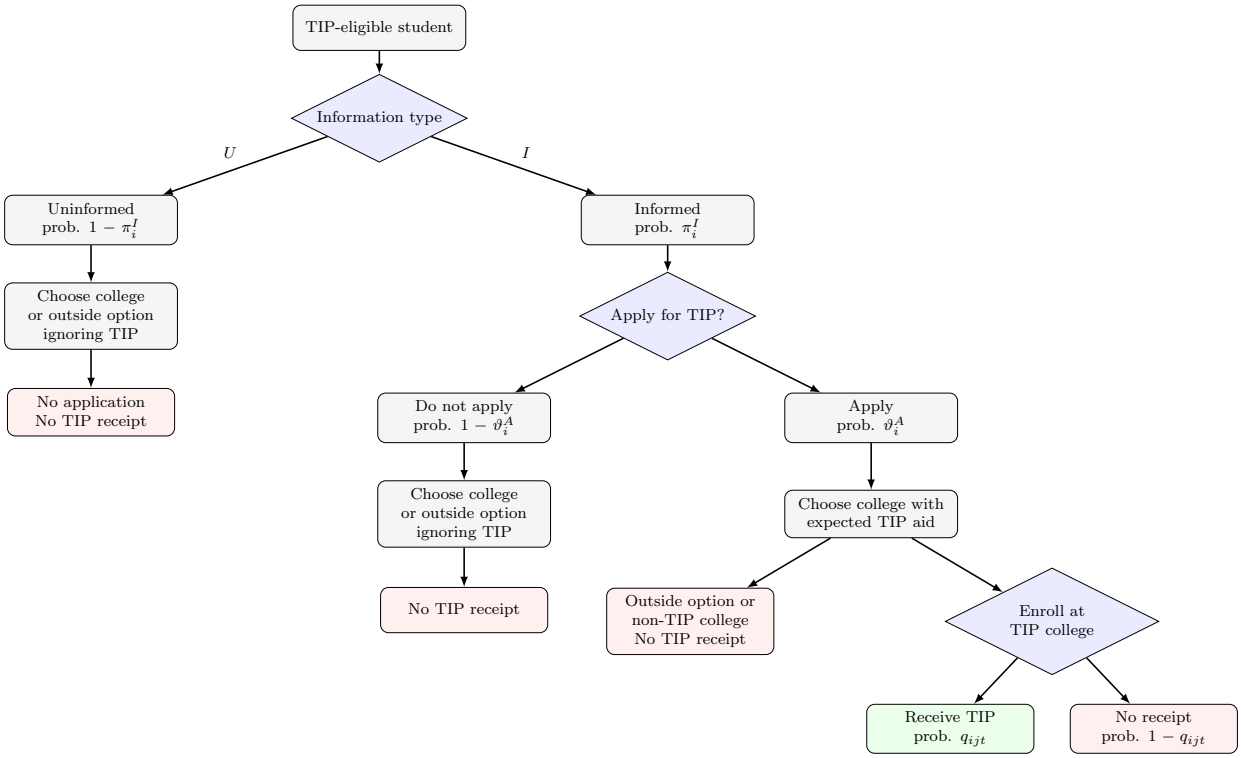
Notes: All models include cohort fixed effects, total months on Medicaid dummies, Medicaid spell dummies, and other baseline controls. Sample is restricted to students with 24 to 96 total months of Medicaid. Robust standard errors in parentheses. All outcomes are measured within 2 years of HS graduation. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 6: Reduced Form Evidence of Incomplete Information

	Spec 1 OLS, full choice set	**Spec 2** OLS, enrolled only	**Spec 3** CMC logit
Tuition & Fees ($000)	-0.00325^{***}	-0.00298^{***}	-0.25222^{***}
	(0.00044)	(0.00057)	(0.0295)
TIP Aid ($000)	-0.00026^{***}	0.00105^{***}	0.00173
	(0.00007)	(0.00006)	(0.00565)
Observations	31,675,130	21,721,016	513,602
H_0: $\gamma = -\gamma$ (p)	0.0000	0.0003	0.0000
Fixed Effects	PSI; CZ×Year	PSI; CZ×Year	—
Controls	Distance	Distance	Distance, PSI

Notes: Spec 1 = OLS on full choice set with PSI and CZ×Year FE; Spec 2 = OLS conditioned on enrollment (outside option removed) with the same FE; Spec 3 = CMC logit on a 2% sample by CZ×Year with additional institutional controls, including state and local appropriations, 150% graduation rate, and acceptance rate. Standard errors in parentheses are clustered at the CZ×Year level. $^{***}p < 0.01$.

Figure 4: Student Decision Tree in the Structural Model



Notes: The figure summarizes the sequence of latent and observed decisions for a TIP-eligible student. Uninformed students do not apply and choose colleges ignoring TIP. Informed students decide whether to apply, then choose among colleges and the outside option. Only informed students who apply and enroll at a TIP-eligible college can receive the scholarship.

Table 7: Structural Parameter Estimates

Parameter	Economic description	Estimate	SE	t-stat
Preferences				
γ	Price sensitivity ($/1000)	0.149	(0.004)	35.24
Γ_{SES}	Price sensitivity × poverty in HS	0.025	(0.002)	16.18
Γ_{test}	Price sensitivity × test score	-0.021	(0.001)	-22.20
ϕ	Distance	-0.0153	(0.0002)	-66.54
α_{2yr}^{test}	2-year utility × test score	0.487	(0.010)	50.12
α_{4yr}^{test}	4-year utility × test score	1.689	(0.013)	127.08
α_{UM}^{test}	UM utility × test score	2.397	(0.031)	78.46
α_{2yr}^{SES}	2-year utility × poverty in HS	-0.513	(0.046)	-11.12
α_{4yr}^{SES}	4-year utility × poverty in HS	-0.364	(0.046)	-7.89
α_{UM}^{SES}	UM utility × poverty in HS	-1.169	(0.054)	-21.64
Type probability (information)				
θ_0	Intercept	-4.355	(0.164)	-26.56
θ_m	Months on Medicaid	0.118	(0.009)	13.59
θ_X	Counselor-to-pupil ratio (×1000)	0.402	(0.115)	3.49
Application costs				
κ_{FAFSA}	FAFSA environment	0.312	(0.115)	2.71
Receipt hazards				
q_0	Baseline receipt hazard	1.000	(0.018)	55.67
λ_{Pell}	Non-Pell hazard	0.106	(0.004)	25.25
λ_{adm}	Low-college-takeup hazard	0.740	(0.035)	21.45

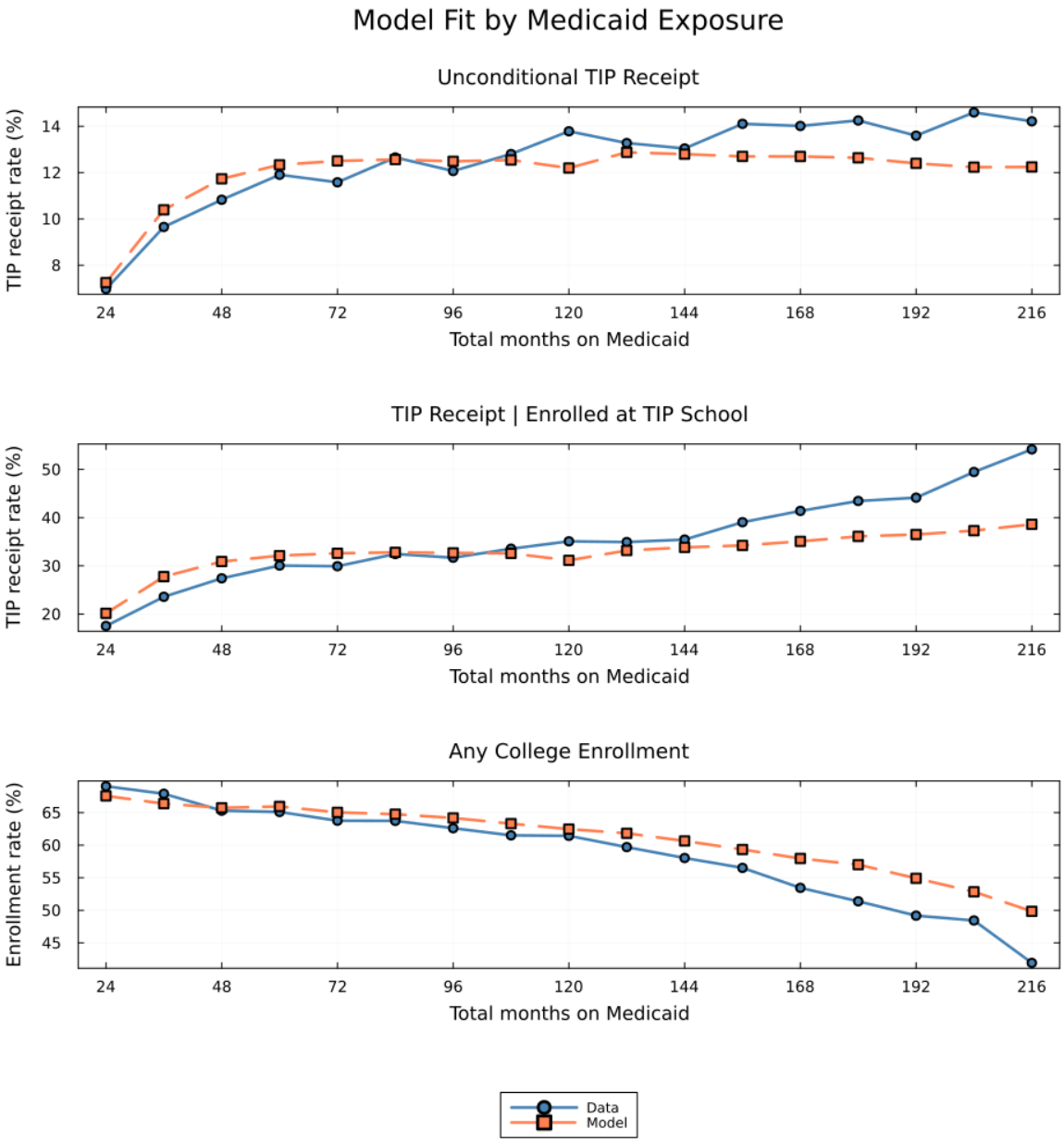
Notes: Estimates are loaded from the saved estimation CSV and evaluated on the model-fit sample ($N = 997,545$). Standard errors and t-statistics are reported when present in the parameter CSV; fixed parameters are marked as fixed.

Table 8: Model Fit Diagnostics

Moment / Pattern	Data	Model
Panel A. Targeted moments		
Enrollment rate*	0.7045	0.7045
2y enrollment rate*	0.2827	0.2827
4y enrollment rate*	0.4218	0.4218
Outside option share*	0.2955	0.2955
Attend any college: TIP eligible	0.0133	0.0159
Attend any college: TIP eligible × months beyond 24	0.0015	0.0007
Receipt at TIP college	0.3437	0.2831
Receipt at TIP college, Pell	0.4528	0.3159
Receipt at TIP college, non-Pell	0.2586	0.2575
Receipt at TIP college, low-takeup colleges	0.2240	0.2417
Receipt at TIP college, high-takeup colleges	0.4686	0.3261
Panel B. Untargeted fit diagnostics		
Received TIP: TIP eligible	0.0409	0.0764
Received TIP: TIP eligible × months beyond 24	0.0027	0.0010
TIP amount received: TIP eligible	234.5000	414.6552
TIP amount received: TIP eligible × months beyond 24	12.8300	8.0231
Enrollment rate among TIP-eligible students	0.5908	0.6142
2-year enrollment rate among TIP-eligible students	0.3038	0.3136
4-year enrollment rate among TIP-eligible students	0.2870	0.3005
TIP receipt rate among TIP-eligible students	0.1255	0.1209
TIP receipt rate among TIP-eligible enrolled students	0.2125	0.1968
TIP receipt rate among TIP-eligible students enrolled at TIP colleges	0.3437	0.3263
TIP-college enrollment share among TIP-eligible enrolled students	0.5886	0.6033
Pell receipt gap	0.1944	0.0584
Panel C. Latent model objects		
Informed share near threshold		0.4763
Mean informed share among eligible		0.9656
Mean application probability among eligible		0.5058
Mean q at aid-positive chosen colleges		0.5711

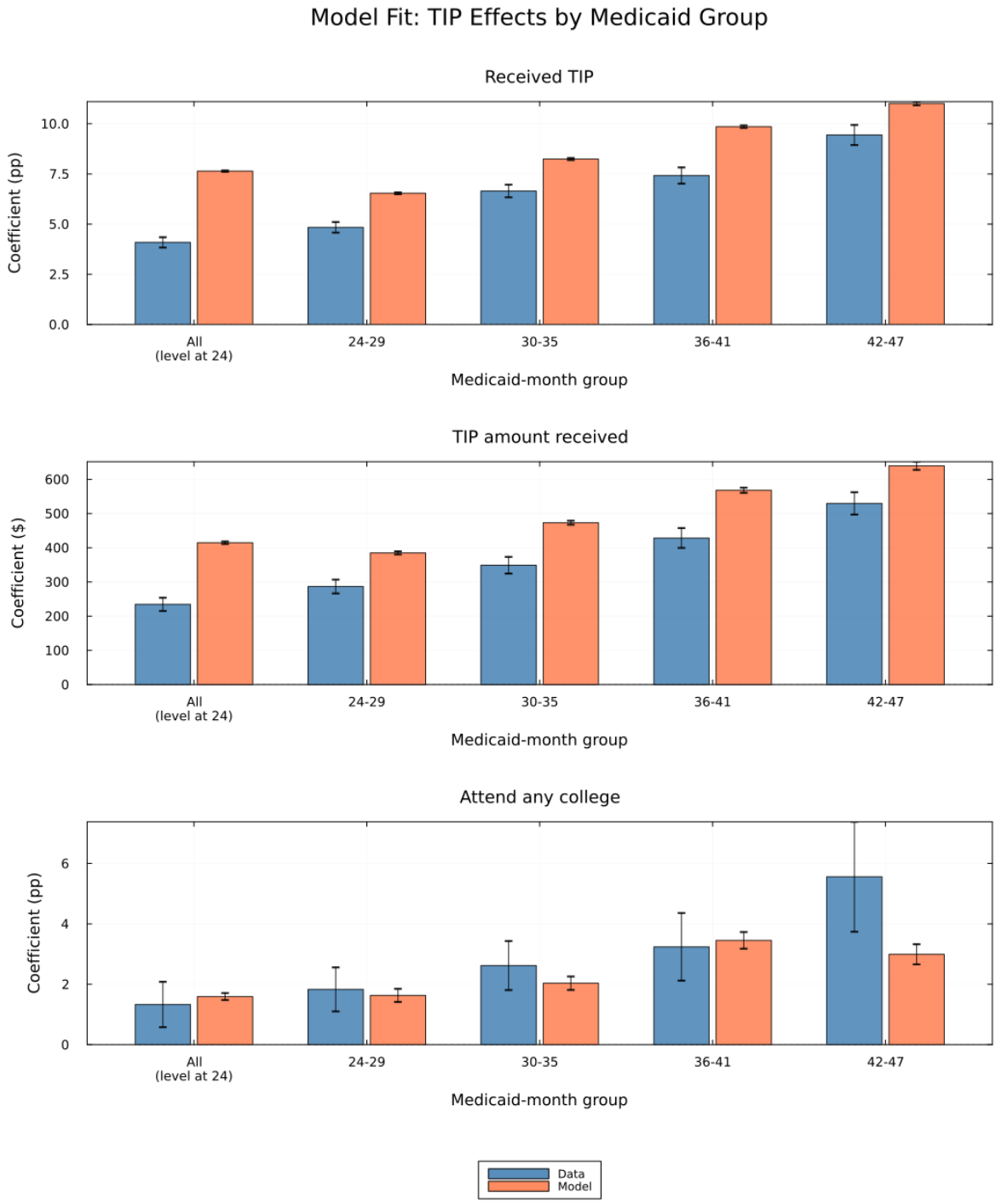
Notes: Panel A lists targeted moments. Rows marked with * are aggregate enrollment shares matched through the BLP inversion for mean utilities, not GMM moments. The official GMM matching targets are the two attend-any-college coefficients from the Medicaid heterogeneity design, restricted to students with 24–96 months of Medicaid. The receipt/compliance rows are the additional GMM receipt moments. Panel B reports untargeted diagnostic fit. Panel C reports latent model objects, so the data column is intentionally blank.

Figure 5: Model Fit by Overall Medicaid Exposure



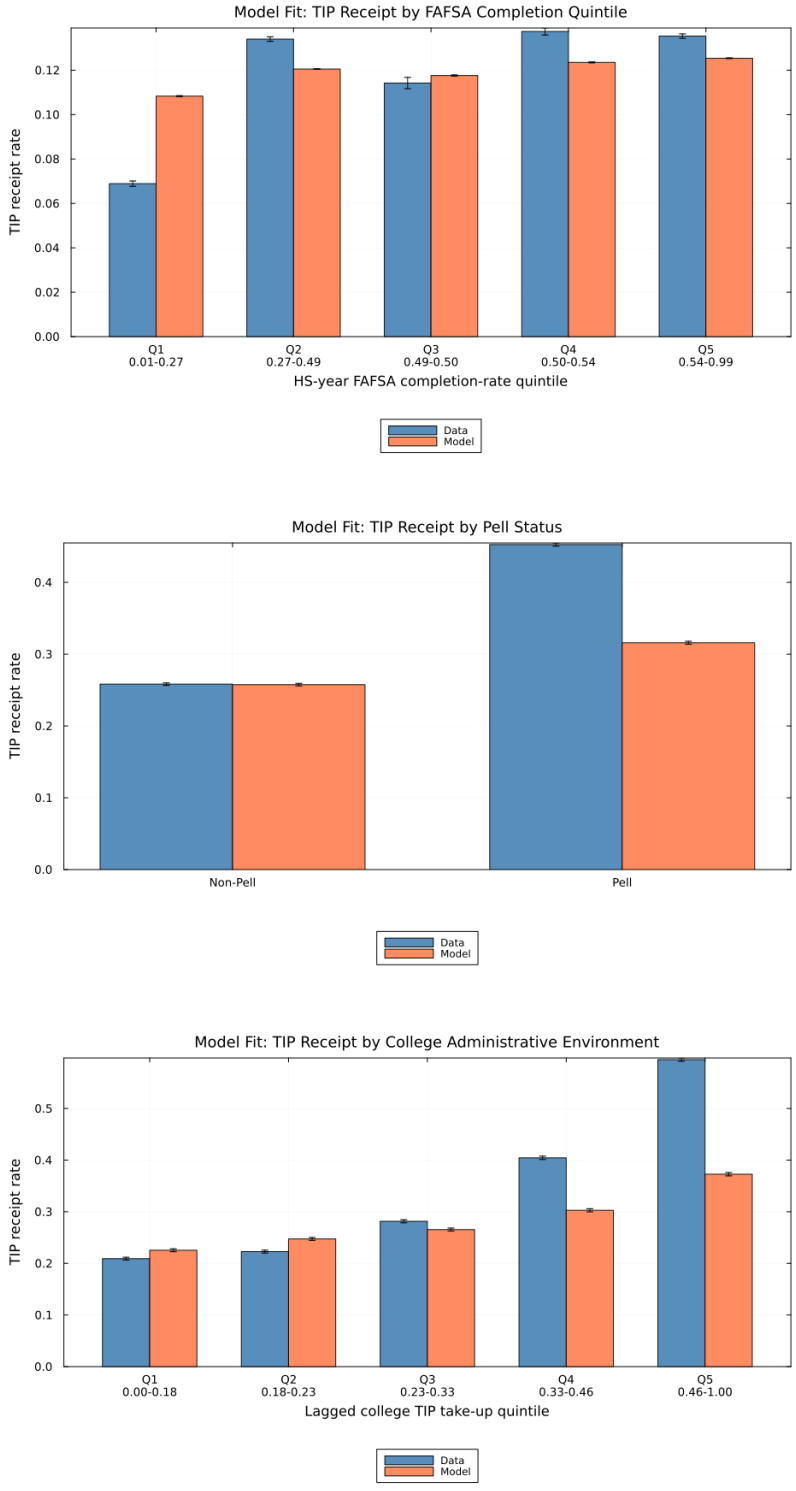
Notes: Figure compares observed and model-predicted TIP receipt and overall enrollment rates by months on Medicaid during childhood (binned) among eligible students in the estimation sample.

Figure 6: Model Fit with Matching Estimates



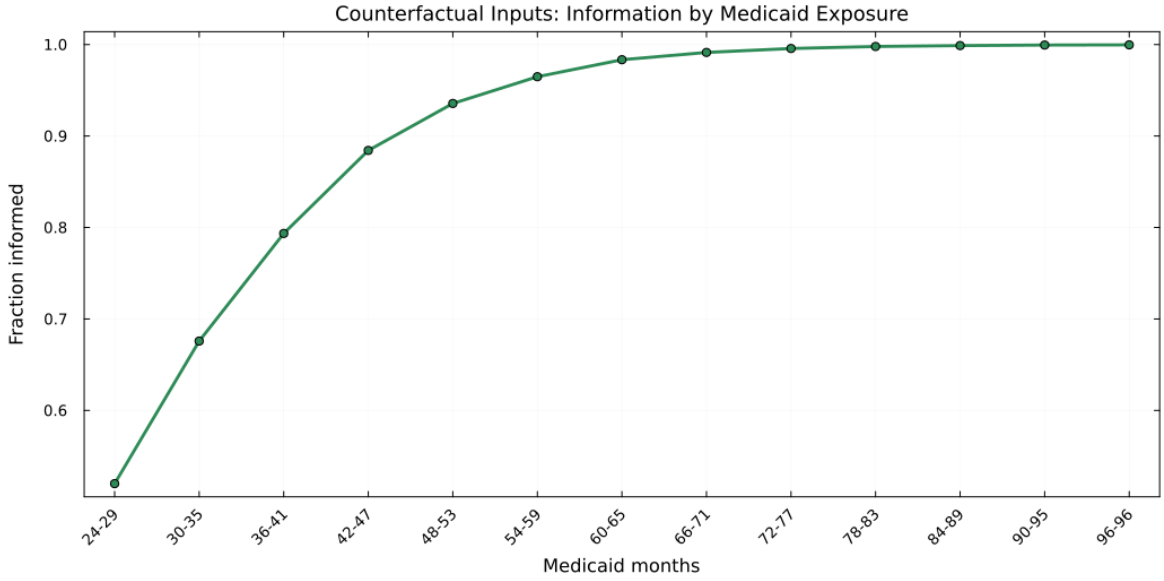
Notes: Figure compares observed and model-predicted reduced-form effects of TIP eligibility on TIP receipt, TIP amount, and overall college enrollment rates by months on Medicaid during childhood (binned) among eligible students in the estimation sample. Reduced form estimates come from all panels of Table 5 columns (1) to (3)

Figure 7: Model Fit on Covariates



Notes: Figure compares observed and model-predicted TIP receipt by three characteristics used in the estimation among TIP eligible students in the estimation sample. The first panel is unconditional on enrollment; the bottom two panels condition on college enrollment.

Figure 8: Share Informed by Months on Medicaid



Notes: Figure reports the predicted share of eligible students that are informed about TIP by total number of months enrolled in Medicaid.

Table 9: Sequential Decomposition: Cost of Frictions

	Total Enrollment		CC Enrollment	
Step	**Rate**	**Δ (pp)**	**Rate**	**Δ (pp)**
Panel A: Enrollment rates and changes across friction removal				
D0: Baseline (all frictions)	0.6163	—	0.3163	—
D1: − Info ($\pi^I = 1$)	0.6174	+0.11	0.3174	+0.11
D2: − Info, App ($\vartheta^A = 1$)	0.6520	+3.47	0.3524	+3.50
D3: Frictionless ($q \uparrow 0.25$)	0.6767	+2.47	0.3940	+4.16
Panel B: TIP effect at each step (scenario − No TIP, in pp)				
D0 (baseline)		+3.65		+3.49
D1 (− info)		+3.76		+3.60
D2 (− info, app)		+7.22		+7.10
D3 (frictionless)		+9.70		+11.26

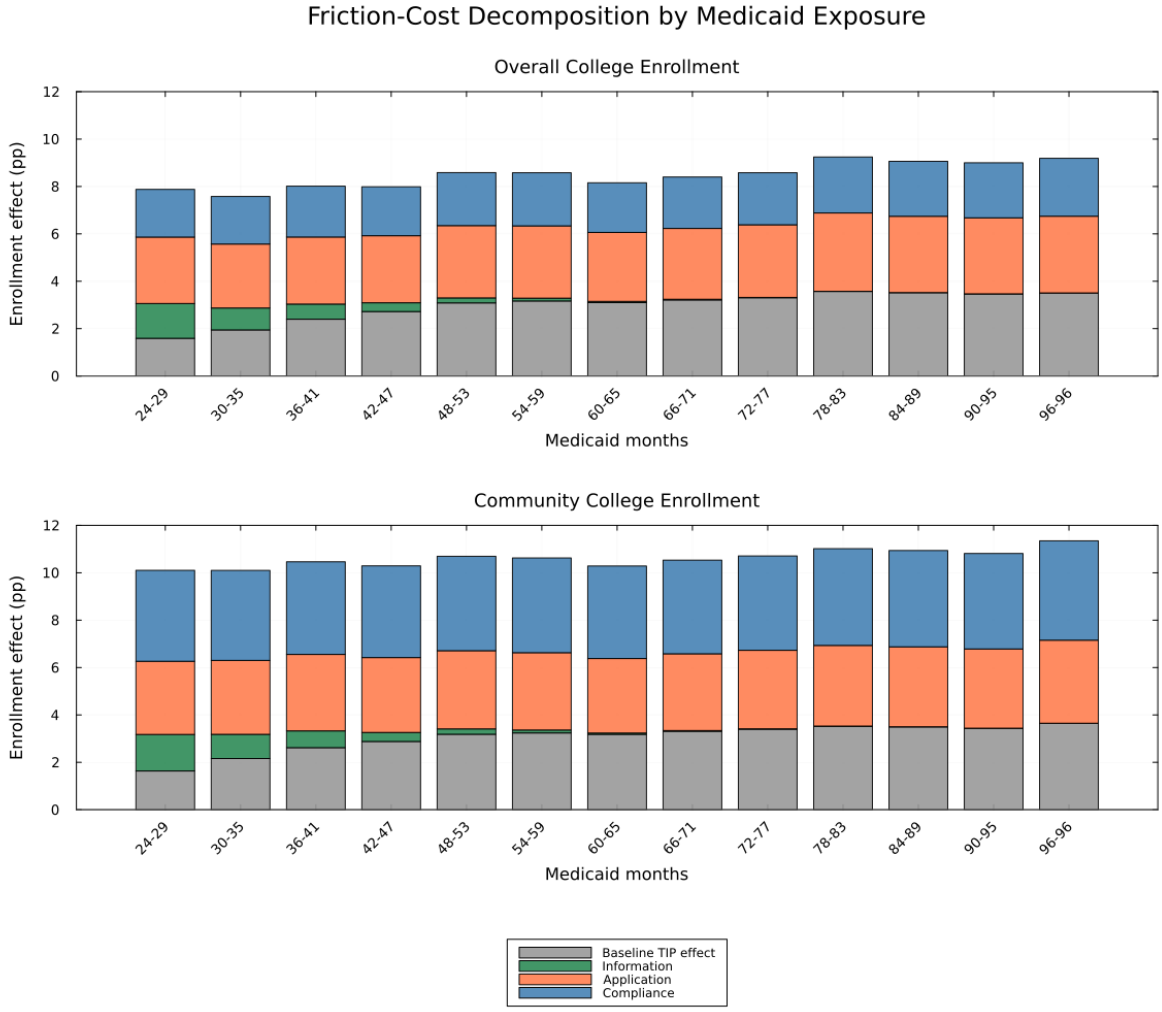
Notes: Counterfactuals use the estimated model on the 50% estimation subsample. The table reports the non-reversed friction-cost decomposition. D0 is the baseline with all estimated frictions. D1 sets $\pi_i^I = 1$. D2 also sets $\vartheta_i^A = 1$. D3 increases q_{ijt} by 0.25 points at all TIP-participating 2-year colleges (up to 1). Panel A reports enrollment rates and incremental changes from the previous step. Panel B reports each scenario's enrollment effect relative to the no-TIP counterfactual.

Table 10: Sequential Decomposition: Threshold Students

	Total Enrollment		CC Enrollment	
Step	**Rate**	**Δ (pp)**	**Rate**	**Δ (pp)**
Panel A: Enrollment rates and changes across friction removal				
D0: Baseline (all frictions)	0.6749	—	0.3088	—
D1: − Info ($\pi^I = 1$)	0.6873	+1.24	0.3219	+1.32
D2: − Info, App ($\vartheta^A = 1$)	0.7149	+2.76	0.3529	+3.10
D3: Frictionless ($q \uparrow 0.25$)	0.7350	+2.01	0.3912	+3.82
Panel B: TIP effect at each step (scenario − No TIP, in pp)				
D0 (baseline)		+1.74		+1.86
D1 (− info)		+2.98		+3.18
D2 (− info, app)		+5.74		+6.28
D3 (frictionless)		+7.75		+10.10

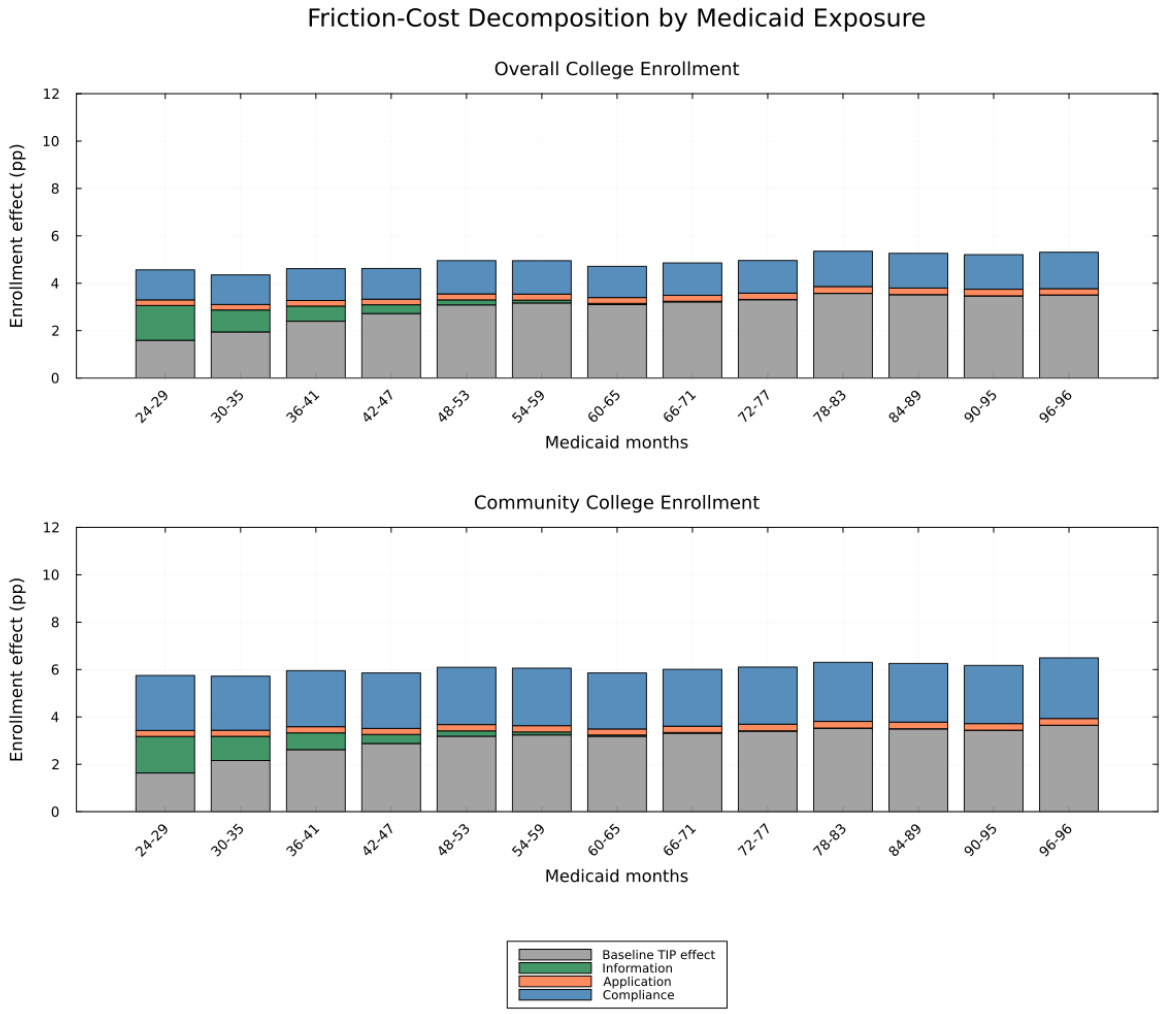
Notes: Counterfactuals are for TIP-eligible threshold students with 24-35 total Medicaid months. The table reports the non-reversed friction-cost decomposition. D0 is the baseline with all estimated frictions. D1 sets $\pi_i^I = 1$. D2 also sets $\vartheta_i^A = 1$. D3 increases q_{ijt} by 0.25 points at all TIP-participating 2-year colleges (up to 1). Panel A reports enrollment rates and incremental changes from the previous step. Panel B reports each scenario's enrollment effect relative to the no-TIP counterfactual.

Figure 9: Simulated Enrollment Effect of TIP With Frictions Removed (Large Application Cost Change)



Notes: Figure reports the simulated treatment effect of TIP eligibility on overall and community college enrollment by total number of months enrolled in Medicaid. Treatment effect is estimated by comparing simulated enrollment with TIP set at its current level vs. setting TIP amount to zero. Baseline is with all frictions present. Subsequent simulations remove frictions sequentially and additively (information, then application costs, then compliance costs). Application cost reduction involves having all students submit an application by setting $\vartheta_i^A = 1$ for all informed students.

Figure 10: Simulated Enrollment Effect of TIP With Frictions Removed (Small Application Cost Change)



Notes: Figure reports the simulated treatment effect of TIP eligibility on overall and community college enrollment by total number of months enrolled in Medicaid. Treatment effect is estimated by comparing simulated enrollment with TIP set at its current level vs. setting TIP amount to zero. Baseline is with all frictions present. Subsequent simulations remove frictions sequentially and additively (information, then application costs, then compliance costs). Application cost reduction involves equalizing costs between high and low FASA high schools by setting $\kappa_{it} = 0$ for all informed students.

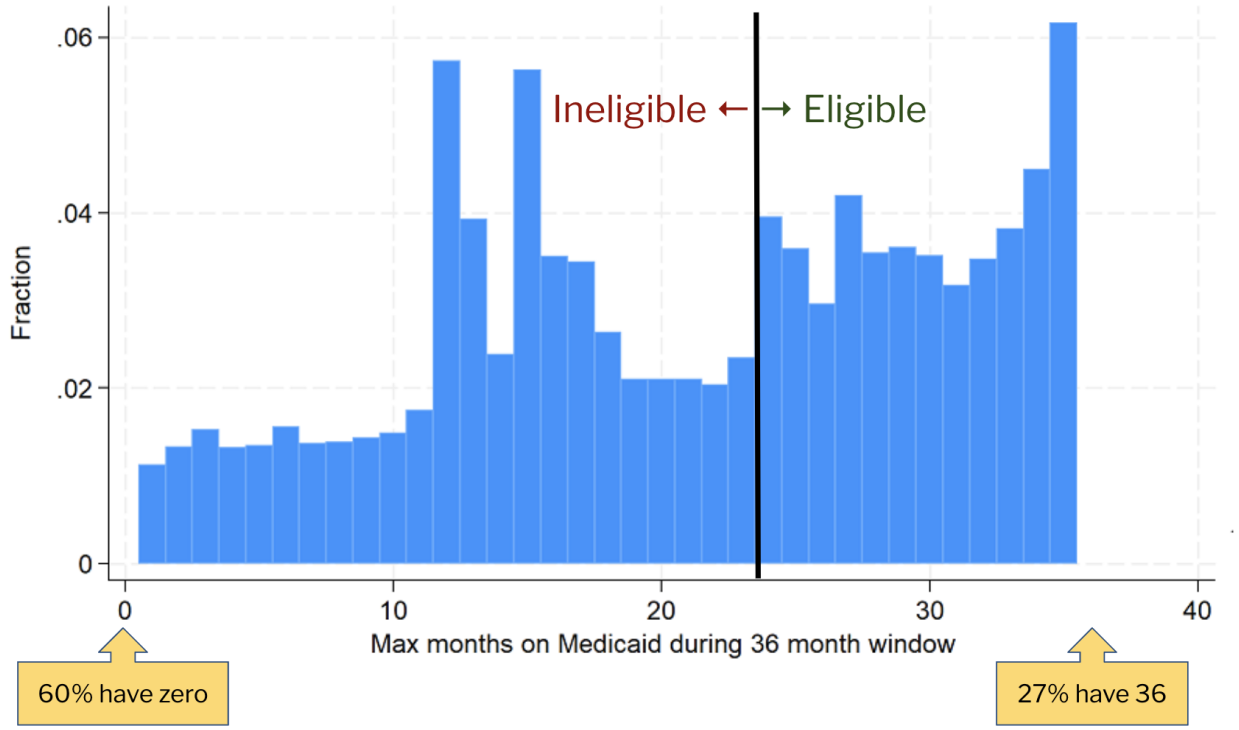
Appendix A. Additional Tables and Figures

Table A1: RD Balance Tests

Variable	Mean	Discontinuity	SE	P-Value
Female	0.51	-0.03	0.015	0.023
White	0.75	0.01	0.013	0.644
Black	0.18	0.00	0.012	0.934
Hispanic	0.07	0.01	0.007	0.475
ACT Score	18.8	-0.3	0.2	0.246
SAT Score	965	13	9	0.158
% of of K12 on FRPL	0.50	0.02	0.013	0.124
Total Months on Medicaid	53.8	-0.8	1.0	0.402
Total Months on TANF	2.7	-0.7	0.3	0.029
Total Months on SNAP	25.3	-0.1	1.0	0.937

Notes: * RD coefficients estimated via local linear regression with optimal bandwidths per Calonico, Cattaneo, and Titiunik (2014, 2015). Means computed on samples selected by the RD bandwidths. Discontinuity column reports RD estimates using each listed variable as the outcome and the TIP eligibility running variable as the regressor. Standard errors are robust.

Figure A1: Distribution of Running Variable



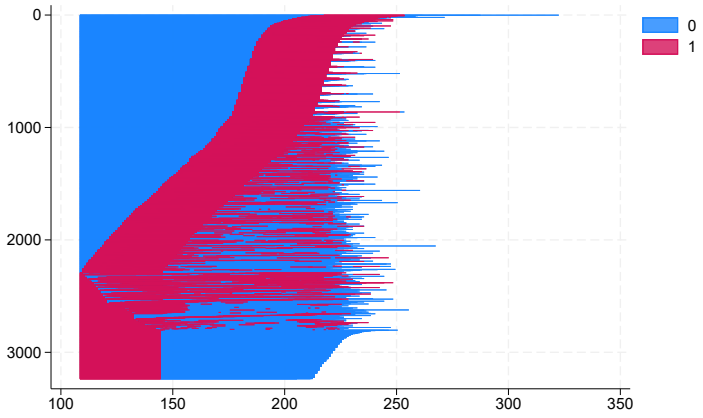
Notes: Figure reports the share of students in each bin of the running variable, which is the maximum number of months on Medicaid across all 36 month windows between age 9 and high school graduation. Sample includes all Michigan high school graduates from 2011 to 2021. Density at 0 and 36 months is not shown due to much larger scale.

Table A2: RD: Robustness

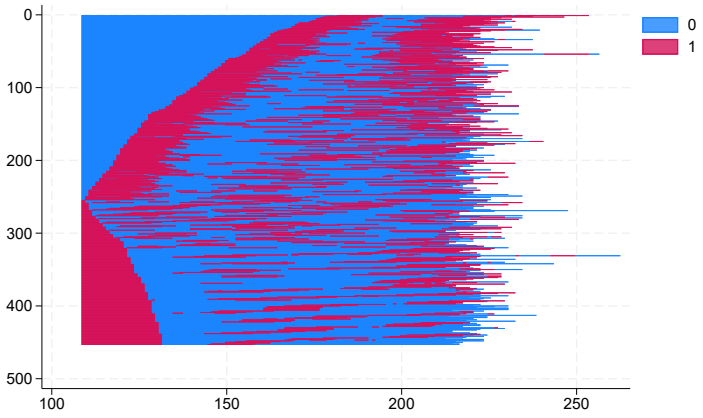
Sample	BW	Kernel	Estimate	Std. Error	p-value
All	Optimal	Triangular	−0.01067	(0.01319)	0.418
1–35 months	Optimal	Triangular	−0.01528	(0.01488)	0.304
1–35 months	4	Triangular	−0.01036	(0.01309)	0.429
1–35 months	4	Uniform	−0.00532	(0.01051)	0.613
1–35 months	8	Triangular	0.00646	(0.00796)	0.417
1–35 months	8	Uniform	0.02015	(0.00696)	0.004

Notes: RD coefficients are estimated using a local linear model with the stated bandwidth. Controls include high school cohort dummies, female, race dummies, foster care, homeless, share of years with free or reduced price lunch, total months on SNAP, total months on TANF, total months on Medicaid, SAT or ACT score. Standard errors are robust.

Figure A2: Matching: Source of Variation



(a) 36 months, TIP Eligible



(b) 36 months, Not TIP Eligible

Notes: Figure indicates the monthly patterns of Medicaid enrollment among students with exactly 36 months of total Medicaid enrollment since age 9 (x-axis = 108) up through the month of high school graduation. Students differ in the number of months included because of variation in their age at graduation, though most students are followed for about 220 months (18 years, 4 months).

Table A3: Matching Balance Tests

	Mean	(1)	(2)	(3)	(4)	(5)
Female	0.514	−0.0136***	−0.0147***	−0.00931*	−0.00844	−0.00652
		(0.00283)	(0.00293)	(0.00534)	(0.00536)	(0.00540)
Black	0.196	−0.0323***	−0.0479***	−0.0162***	−0.00833**	0.0104**
		(0.00221)	(0.00229)	(0.00410)	(0.00410)	(0.00407)
Poverty ratio	0.453	0.116***	0.0789***	−0.0164***	−0.00860**	0.00613*
		(0.00195)	(0.00202)	(0.00363)	(0.00361)	(0.00359)
SAT	985	−8.252***	−6.329***	−0.209	−0.749	−1.834
		(0.694)	(0.735)	(1.103)	(1.107)	(1.117)
ACT	19.5	−0.0988***	−0.00905	0.155***	0.134***	0.0562
		(0.0172)	(0.0176)	(0.0377)	(0.0377)	(0.0380)
Cohort FE		Yes	Yes	Yes	Yes	Yes
Total Months Medicaid Dummies		No	Yes	No	Yes	Yes
Since Age 9 Months Medicaid Dummies		No	No	Yes	Yes	Yes
Medicaid Spells		No	No	No	No	Yes
Controls		No	No	No	No	No

Notes: Sample is restricted to individuals with 24 to 96 total months on Medicaid in childhood.