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Success Begets Success: The Dynamic Treatment Effects of Financial Aid Tournaments

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Financial aid programs in higher education vary widely in design, including how aid is structured and the timing of provision. This paper studies the impact of financial aid provided as a repeated tournament and its dynamic treatment effects. Pooling administrative data that captures 32% of all tertiary students in a single European country, I exploit a relative GPAbased eligibility rule in a regression discontinuity design to estimate the causal impacts of two types of aid: tuition waivers and stipends. Both forms of aid yield large returns; waiver (stipend) eligibility increases graduation rates by 12.4 (6.6) percentage points, and increases student next-semester GPA by 0.38 (0.21) standard deviations. I find a powerful crowding-in effect, where receiving aid in one semester significantly increases the probability of receiving it in the future, driving a substantial portion of the total long-term benefit. Exploring tournament heterogeneity reveals a distinct life-cycle of aid: early-semester awards appear to be most effective, with the effectiveness diminishing in later semesters. Finally, I show that while short-term tournament incentives exhibit dynamic complementarity by maximizing the effort of high-achieving students, the long-term impact on degree attainment is deeply compensatory for lower-achieving students. These findings reveal a dualmargin response: while competitive aid incentivizes academic effort from top performers, its long-term impact operates by retaining and graduating marginal students.

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Abstract

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Exploring tournament heterogeneity reveals a distinct life-cycle of aid: early-semester awards appear to be most effective, with the effectiveness diminishing in later semesters. Finally, I show that while short-term tournament incentives exhibit dynamic complementarity by maximizing the effort of high-achieving students, the long-term impact on degree attainment is deeply compensatory for lower-achieving students. These findings reveal a dual-margin response: while competitive aid incentivizes academic effort from top performers, its long-term impact operates by retaining and graduating marginal students.

JEL Classification: H52, H4, I21, I22, I23, I28

Keywords: Student Financial Aid, Higher Education

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1 Motivation

Governments worldwide invest substantial public resources in higher education, viewing it as a primary engine for producing the human capital that drives modern economic growth (Deming, 2022). Many talented individuals are credit-constrained and cannot finance the optimal level of education on their own, and the social returns to education often exceed the private returns, leading to underinvestment without public support. To address these issues, countries spend vast sums on student aid; in the United States alone, this figure reached $256 billion in the 2023-2024 academic year (Ma et al., 2024).

Despite this massive scale of investment, our understanding of aid's long-term effectiveness is clouded by the complexity of real-world policy environments. In most developed economies, students navigate a fragmented landscape of interacting federal, state, and institutional aid programs. This fragmentation creates a central identification challenge: fiscal crowd-out. An exogenous increase in one source of aid often mechanically reduces aid from other sources - a phenomenon that is typically unobserved by the economist (Denning et al., 2019; Eng & Matsudaira, 2021). Consequently, estimates from these multi-program contexts capture a net effect that conflates the behavioral response to aid with the mechanical displacement of other resources, potentially obscuring the dynamic crowd-in effects of financial support.

This paper overcomes these challenges by exploiting a unique natural laboratory in Latvia. Unlike the noisy multi-payer systems of the US or UK, the Latvian higher education system utilizes a tournament-style funding model where competitively reassigned government aid is the sole source of support for more than 90% of students. Furthermore, students follow a fixed curriculum, mitigating the risk of strategic course selection. This institutional clarity creates an opportunity to isolate the pure incentive effects of aid and to causally decompose the total long-term impact of an award into its distinct dynamic components without the confounding bias of unobserved substitution.

My analysis is guided by a conceptual framework that synthesizes four key elements.

First, policymakers are interested in ensuring that students both accumulate human capital and persist in their studies, posing a central tournament design challenge: eliciting maximum effort while preventing dropouts. Second, students are credit-constrained, which leads them to underinvest in their own human capital (Becker, 1964; Lochner & Monge-Naranjo, 2012; Rosen, 1976). Third, financial aid is allocated via a rank-order tournament, an intervention that simultaneously alleviates these binding constraints for winners and creates powerful performance incentives for all competitors (Lazear & Rosen, 1981; Rosen, 1986). Fourth, the repeated nature of this tournament creates a dynamic feedback loop. I posit a crowd-in mechanism where winning aid in one period improves a student's performance, thereby endogenously increasing their probability of winning aid in subsequent periods.

To isolate these mechanisms, I pool administrative student-level panel data from the two largest public universities in Latvia, capturing 198,286 student-semester observations across 32% of all tertiary students in the country. My identification strategy exploits the institutional rule that allocates aid based on GPA rank within a cohort in a regression discontinuity design. As the probability of aid receipt changes discontinuously at the cutoff, I use this variation as an exogenous instrument for aid receipt. I then implement a dynamic RD decomposition method (Biasi et al., 2024; Cellini et al., 2010; Taylor, 2014) to recursively estimate two key parameters: the total long-term effect of an initial aid award, and the effect of the subsequent aid it crowds in.

I find that competitively reassigned aid has large and significant total effects on student success. Receiving a tuition waiver impacts both the extensive and intensive margin, increasing student GPA by 0.41σ and graduation by 14 percentage points (pp). Stipend receipt further impacts academic trajectories, increasing GPA by 0.28σ and graduation rates by 7.9pp. These effects reside at the upper end of those found in the prior literature (Dynarski et al., 2023; Nguyen et al., 2019), highlighting the power of aid in a setting with strong incentives and limited outside options. My dynamic decomposition reveals that the crowd-in of future aid effect is a substantial driver of these large long-term benefits.

By employing the dynamic complementarity framework (Cunha & Heckman, 2007), I find that the interaction between tournament incentives and human capital accumulation varies starkly across margins. For short-term academic performance, the tournament exhibits traditional dynamic complementarity, acting as an effort multiplier for high-achieving students. However, for ultimate degree attainment, financial aid is deeply compensatory. Rather than simply compounding the success of the already-resourced, the long-term value of the tournament lies in disproportionately retaining and graduating marginal, struggling students who would otherwise drop out.

Furthermore, exploring the heterogeneity of these static effects reveals two distinct aspects of financial aid design. First, security fundamentally alters treatment effects: while stipends act as a vital retention tool for students without guaranteed funding, guaranteed waivers actually induce a complacency effect, where winning an additional stipend has a significantly lower impact on academic effort for students who hold guaranteed tuition waivers. Second, there is a distinct life-cycle to financial aid: early-career awards act primarily as a retention mechanism that prevents dropout, while late-career awards act almost exclusively as mechanisms that elicit academic effort.

This paper makes two primary contributions. First, to the literature on student financial aid (Dynarski et al., 2023; Nguyen et al., 2019) and student financial aid design (Burland, 2023; Montalbán, 2022), I provide causal estimates of a financial aid crowd-in mechanism. By measuring these dynamics in a clean policy environment, I estimate the full potential of aid and suggest that static analyses in more complex settings may underestimate the total value of these programs.

Second, I contribute to the literature on tournament theory (Bull et al., 1987; Drago & Garvey, 1998; Lazear & Rosen, 1981). The educational competition studied here serves as a unique natural laboratory with objectively measured performance, explicit rules, and high stakes. The analysis of the crowding-in effect empirically measures the option value of winning an early stage of a multi-period competition (Rosen, 1986). Finally, by integrating the concept of dynamic complementarity, I show how tournament incentives interact with human capital accumulation to produce a dual-margin response: while competitive aid can act as a dynamic complement to elicit short-term effort from high performers, its ultimate long-term value lies in retaining marginal student competitors.

2 Institutional Background and Data

The higher education system in Latvia is concentrated, with the three largest public universities enrolling half of the 76,000 total students in the country. The funding system is organized based on the dual-track tuition model, wherein some students receive tuition waivers and all other students pay full tuition. This model is common throughout all but one of the post-Soviet countries, as well as in some postsocialist countries in Central and Eastern Europe (Smolentseva, 2020).

In Latvia, the primary forms of student financial aid are merit-based government stipends and tuition waivers for students.[1] Tuition waivers are provided to 41% of all students, and 13% of all students received stipends in 2017. In the same year, only 2.8% received financial aid from any other source. Nearly half of the students get no financial aid.

The tuition waivers are allocated to specific programs and cohorts, creating financial aid tournaments for tuition waivers and stipends within cohorts. The government-provided financial aid for a large group of students is regularly reassigned - tuition waivers are assigned for the rest of the academic year, and stipends are assigned for one semester. All students who study in full-time programs for which the government provides waivers have a chance of acquiring a tuition waiver for the next semester. Students who receive tuition waivers also have the opportunity to compete for stipends. These stipends are

[1] Within the OECD, about half of the countries offer scholarships awarded on the basis of primarily merit (OECD, 2022).

paid out to students as direct money transfers to their bank accounts every month for the duration of the stipend.

The government requires the aid it provides to be allocated based on merit. Merit for incoming students is defined as their performance in high-school exit exams. The students with the best grades in the exams are rank-ordered within their admitted program and receive tuition waivers. In subsequent semesters, institutions have freedom to define merit as GPA with an optional addition of other characteristics such as research output.

Tuition waivers and stipends are also extensively available, with roughly half of the bachelor's and master's students in public universities receiving tuition waivers and 9% of undergraduate students and 7% of graduate students receiving stipends. The average student in 2022 had a total monthly expenditure of €1'356, of which tuition fees for the average full-time fee-paying student comprised €313 (Koroļeva et al., 2022).[2]

The stipends are meant to be disbursed to the highest-achieving students receiving tuition waivers. These stipends pay EUR 99.60 per month for the five-month duration of the semester. This stipend gets deposited into the student's bank account. The stipends cover roughly 10% of the average student's monthly expenses, excluding tuition.

Students within Latvian higher education typically follow a predetermined sequence of courses each semester, a common characteristic of many European higher education systems. This fixed curriculum means that academic competition for aid occurs over a common set of academic requirements for all students in a cohort.

The student financial aid assignment mechanism is visualized in Figure 1.

I pool administrative data from the two largest public universities in the country: the University of Latvia (UL) and Riga Stradiņš University (RSU). Together, these institutions enrolled roughly 32% of all tertiary students in Latvia in 2022. UL operates as a classical university offering a broad spectrum of programs under the Ministry of Education and Science, while RSU is a highly specialized institution focused primarily on healthcare

[2]The other top monthly expenditures were board (€372), room (€365), and transportation (€106).

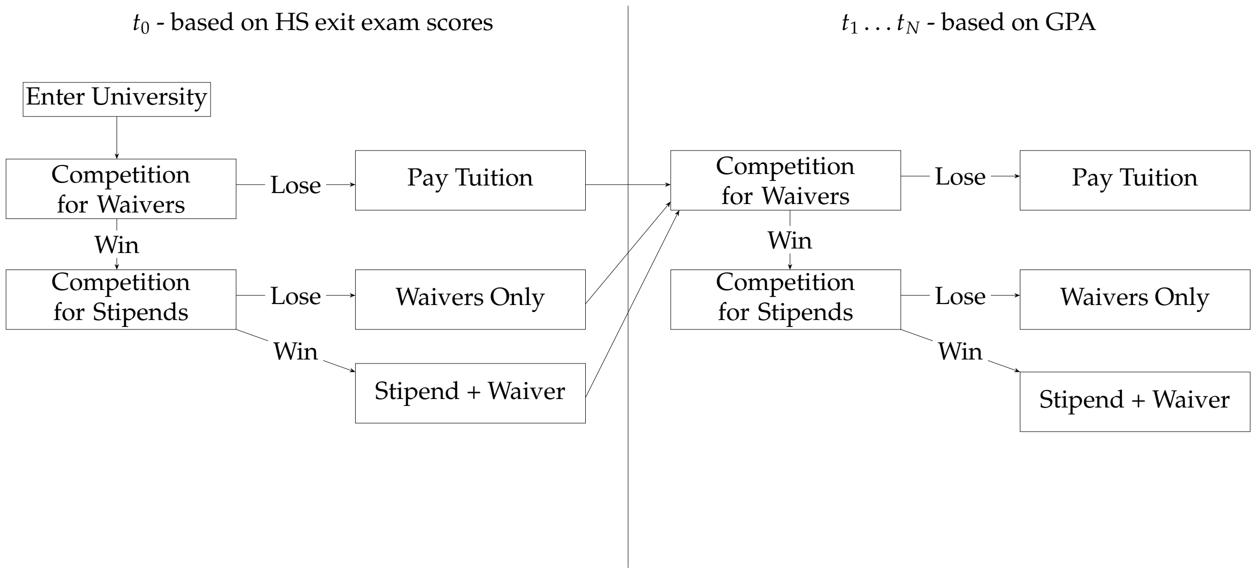


Figure 1: The Student Financial Aid Assignment Mechanism in a Dual-Track Tuition Model

studies under the Ministry of Health.

While their academic focus and average student demographics differ slightly, both universities operate under the exact same financial aid structure. Both employ a dual-track tuition model where competitively reassigned government aid - tuition waivers and stipends - acts as the primary, and often sole, source of financial support. While there are minor institutional variations in the exact mechanics of aid assignment (for instance, UL utilizes a strict GPA cutoff for stipends, whereas RSU incorporates secondary criteria such as undergraduate scientific output), the underlying tournament dynamics remain identical.

2.1 Data

For the RSU sample, I have data on students in all bachelor's and master's healthcare programs from 2015 to 2022, a total of 33,269 unique students that are observed each semester. This data includes semester-by-semester information on the grades, program, semester, year, graduation, tuition waiver, and stipend status of the students, as well as limited demographic characteristics such as gender, age, and school attended.

For UL, I employ data from 2010 to the second half of 2020. I use data for all tuition-waiver-receiving students for a total of 63 925 student-semester observations. One challenge with the UL data is that it is only available for students who are eligible for stipends (meaning those who received waivers), and I do not observe students who are on both sides of the waiver reception margin.

Using student secondary school data, I further create two demographic variables - whether a student attended a school that provides instruction in a minority language, and whether the school is located in the capital. In Latvia, Latvian language proficiency is a significant requirement for reception of aid (waivers and stipends are only provided in Latvian-language programs), and plays an extremely important role in the job market. Regional disparities are very high in Latvia, with the capital being considerably richer and having a higher level of GDP per capita than other regions. These two variables act as proxies for students' social and economic status.

Table 1 provides the descriptive statistics for the Stipend and Waiver Marginal Samples. The stipend sample pools together data from two universities, and the waiver sample has data only for RSU. Students at the stipend margin are slightly younger on average (22.35 years versus 23.14 years) and marginally more likely to be male (0.22 versus 0.15) and originate from minority-language schools (0.14 versus 0.12). Meanwhile, the demographic characteristics of students at the waiver margin are very similar to the full waiver population, with both groups showing high rates of persistence (0.95) and similar distributions across age and geographic origin.

The institutions do not store data on whether a student applied for a tuition waiver or stipend and their final evaluation in points after combining the GPA with other criteria. This creates measurement error, as I only observe one of the components of the full running variable that is used to assign aid. The potential rank of each student is calculated based on only their GPA and whether they are eligible to apply for the scholarship or not.

The institutions also do not store data on a student's admission score. However, I ob-

Table 1: Summary Statistics for Combined Sample

	Stipends - Full			Stipends - Marginal			Waivers - Full			Waivers - Marginal		
Variable	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N
GPA	0.00	0.97	161059	0.32	0.86	39979	−0.28	0.98	3024	−0.25	0.95	1687
Persisted	0.71	0.45	198286	0.76	0.43	39979	0.95	0.21	3024	0.95	0.21	1687
On Track	0.66	0.47	197629	0.65	0.48	39862	0.96	0.21	3023	0.95	0.21	1686
Graduation	0.60	0.49	156412	0.68	0.47	35953	0.80	0.40	1928	0.80	0.40	1142
Graduation OT	0.45	0.50	155632	0.52	0.50	35920	0.69	0.46	1928	0.68	0.47	1142
Aid	0.13	0.34	198286	0.34	0.48	39979	0.40	0.49	3024	0.44	0.50	1687
Male	0.15	0.35	194979	0.22	0.41	39243	0.15	0.36	3024	0.13	0.34	1687
Age	23.14	6.17	177231	22.35	4.98	38895	21.78	5.90	2969	21.93	5.89	1659
Minority	0.12	0.32	174821	0.14	0.34	38130	0.16	0.36	2969	0.15	0.35	1659
Capital	0.40	0.49	174821	0.43	0.50	38130	0.41	0.49	2969	0.40	0.49	1659
Math	71.64	18.18	23178	73.26	18.11	10134	–	–	–	–	–	–

Note: The table reports summary statistics for individual-semester dyads. Math represents the high school exit exam percentage and is only available for the UL sub-sample.

serve whether a student received a waiver upon enrollment and student GPA, permitting me to evaluate the impact of aid in subsequent semesters after enrollment.

The students compete within their cohorts in a given semester, year and program - the risk set. As the programs are standardized with students taking a pre-determined list of courses in pre-determined semesters, if a student does not complete their semester, they will have to retake their semester and thus be moved to a lower cohort. The risk set is dynamic and changes every semester for a student as they might fall behind, stop out, or they might have students who fell behind or stopped out come into their risk set.

I group individuals by risk sets and then take the subset of individuals who are eligible for each type of financial aid. For stipend risk sets, these are individuals who have received tuition waivers, as it is a precondition for eligibility. For tuition waiver risk sets, these are individuals who did not receive tuition waivers upon enrollment.

As the stipends are assigned based on rank order, I create a running variable that is based on rank and recenter it around the last person to have received financial aid so that the individual who received aid with the lowest rank in their risk set is at 0. I standardize student GPA by risk set to account for more or less difficult semesters and programs.

3 Estimating the Impact of Financial Aid

Separating out the direct treatment effects and dynamic treatment effects requires using both a regression discontinuity design and a dynamic regression discontinuity design. The regression discontinuity design provides me with estimates of the impact of aid that include the impact of aid crowding in future aid. The dynamic regression discontinuity design allows me to separate the impact into the marginal effect and the crowding-in effect of aid while holding future aid receipt constant.

The identification strategy exploits the institutional rule whereby eligibility for tuition waivers and stipends is determined by a student's rank based on academic performance

(GPA) relative to a cutoff within a defined program-cohort-semester risk set. This rule generates discontinuities in the probability of aid eligibility at the cutoff rank, providing quasi-experimental variation that can be used by an RD design.

To recover the estimates of the effect of various types of aid on student outcomes, I use a regression discontinuity design that compares students just below and just above the grade cutoff. The identifying assumption of my estimation strategy is that potential outcomes are continuous throughout the cutoff, i.e. that they do not discontinuously jump (Lee & Lemieux, 2010). This means that students near the rank cutoff are comparable in their potential outcomes regardless of reception of treatment, allowing me to estimate the effect of the provision of a tuition waiver or stipend on their academic outcomes.

3.1 Estimating the Total Impacts of Aid

I first begin by estimating the total impacts of aid receipt on student outcomes. Let r_{ijt} denote the rank of student i in risk set j during semester t, and let $Above_{ijt}$ be an indicator variable equal to 1 if r_{ijt} meets or exceeds the cutoff rank c_{jt} (i.e., $r_{ijt} \geq c_{jt}$, assuming higher rank is better) and 0 otherwise. The rank r_{ijt} serves as the running variable. The central identifying assumption is the continuity of potential outcomes at the cutoff c_{jt}, conditional on the running variable (Lee & Lemieux, 2010). Under this assumption, students near the cutoff are comparable, differing primarily in their aid eligibility status induced by the discontinuity.

I use rank as the running variable as that is the one that most closely mirrors the assignment mechanism. I empirically validate this, with rank as the running variable having the strongest predictive power of aid receipt at the cutoff. The main challenge with using rank as the running variable is that it is explicitly discrete. However, using GPA has the same challenges.

I employ local linear regression to estimate the Intent-to-Treat (ITT) effect of aid eligibility on outcomes measured k semesters after the competition ($Y_{i,t+k}$). This generic framework is used to estimate both immediate next-semester outcomes (such as next-semester GPA and) long-term cumulative outcomes (such as graduation). The reduced-form model is estimated as:

$$Y_{i,t+k} = \alpha + \delta^{T}_{t,t+k} Above_{ijt} + f(r_{ijt}) + \theta_{jt} + \epsilon_{ijt} \tag{1}$$

where $f(r_{ijt})$ is a linear function of rank, and θ_{jt} represents risk set fixed effects. The parameter $\delta^{T}_{t,t+k}$ captures the total effect of initial eligibility. For immediate next-semester outcomes ($k = 1$), no intermediate competitions occur, meaning this total effect captures the pure marginal impact of the initial award. For long-term outcomes ($k > 1$), this total effect amalgamates both the direct impact of the initial award and any indirect effects mediated through changes in subsequent aid eligibility.

While the reduced-form estimates capture the policy impact of eligibility, compliance at the threshold is imperfect. To recover the Local Average Treatment Effect (LATE) of actual financial aid receipt, I estimate a fuzzy regression discontinuity design via Two-Stage Least Squares (2SLS). I utilize cutoff eligibility ($Above_{ijt}$) as an exogenous instrument for the financial aid received (Aid_{ijt}). I then conduct additional analysis to get the per-euro impacts by replacing Aid_{ijt} with the amount of financial aid received in thousands of Euros.

The first-stage equation models the amount of aid received as a function of crossing the cutoff:

$$Aid_{ijt} = \alpha_1 + \gamma_1 Above_{ijt} + f_1(r_{ijt}) + \theta_{jt} + \nu_{ijt} \tag{2}$$

The fitted values from the first stage ($\widehat{Aid}_{ijt}$) are then used in the second-stage equation to estimate the causal impact of aid receipt, as well as the impact of €1,000 in financial aid receipt on the respective outcome:

$$Y_{i,t+k} = \alpha_2 + \beta_1 \widehat{Aid}_{ijt} + f_2(r_{ijt}) + \theta_{jt} + \varepsilon_{ijt} \tag{3}$$

For β_1 to represent an unbiased causal estimate, the instrument must satisfy the exclusion restriction, requiring that crossing the eligibility threshold impacts future academic outcomes only through the allocation of financial aid. The primary theoretical threat to this assumption in a rank-order tournament is a localized discouragement effect, or the sore loser problem. If students who narrowly miss the cutoff observe their exact marginal failure, they may experience a psychological penalty and subsequently reduce their academic effort. Such a behavioral response would violate the exclusion restriction, as the cutoff would directly impact outcomes independently of aid receipt.

However, the institutional design of the Latvian allocation mechanism mitigates this threat. The tournament is effectively blind: while students know their own GPA, they are not provided with the scores of their peers, their exact rank within the dynamic risk set, or the ex-post cutoff location. Because students cannot precisely observe how close they were to the margin, it is highly improbable that psychological discouragement jumps discontinuously precisely at the threshold, preserving the validity of the exclusion restriction.

I use data-driven bandwidth selection (Calonico et al., 2020) and robust standard errors clustered at the student level. I then perform standard RD validity tests, including density continuity tests (McCrary, 2008) and covariate balance tests to assess the plausibility of the identifying assumption.

For RSU, given the less sharp cutoff, this approach does not create a perfect threshold, as individual applications and their scores by the committee deciding on aid are not observed. At the same time, for UL, given that aid is provided only based on GPA, the cutoff is sharp.

There are several threats to validity to this approach. The first threat is that students could for some reason have different potential outcomes across the threshold. Although I cannot empirically test this assumption, I can build intuition on it by testing whether the observed characteristics of students are continuous throughout the cutoff. Table 2 reports

Table 2: Balance Test

	Stipends	Waivers
Male	0.003	−0.017
	(0.007)	(0.031)
Age	0.137	0.310
	(0.085)	(0.408)
Capital	0.014	−0.063
	(0.010)	(0.047)
Minority	0.005	0.017
	(0.006)	(0.034)
Risk Set FE	X	X
Num.Obs.	39 241	1864

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

Note:
The table reports bias-corrected robust RD estimates using OLS with risk set fixed effects.

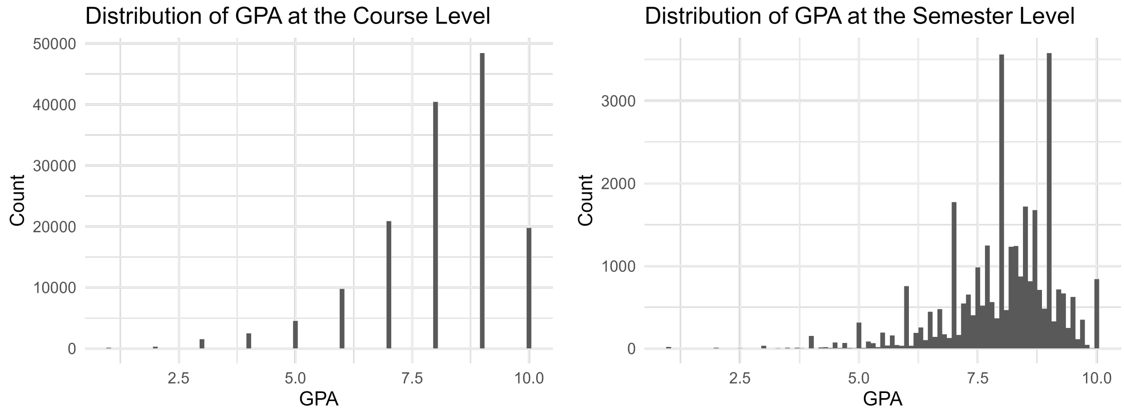
the result of the balance test for stipends and waivers respectively. What I find is that students' demographic characteristics do not vary discontinuously across the threshold.

The second threat is that students could potentially self-select into receiving aid. This would lead to individuals above the cutoff being qualitatively different from those below it, meaning that they would not be comparable. In my context, this would require two things - that students choose whether to apply or not apply for aid and that they can precisely manipulate or tell what their grades and rank will be in their group.

Although students can choose to apply or not for a scholarship, this condition is necessary but not sufficient to invalidate this approach. To be able to perfectly self-select, the students would need to have perfect information on the GPA of their cohort mates and whether their cohort mates will apply for aid or not. The institution does not provide information for students on the grades of their peers and their rank in their group.

An alternative risk is that administrators could potentially selectively encourage students to apply for financial aid. For example, administrators might discriminate against individuals based on their characteristics and specifically encourage certain groups to ap-

Figure 2: Raw GPA at the Course and Semester Levels



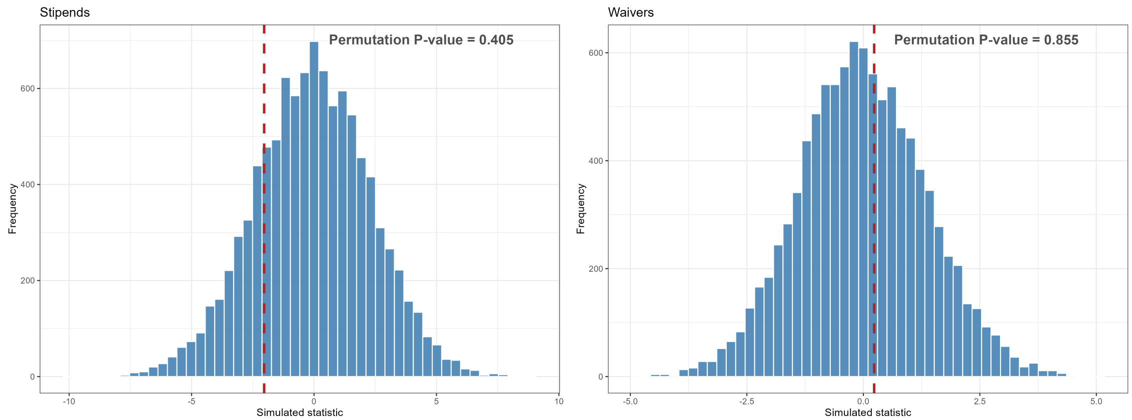
Note: The figure on the left shows the raw GPA that students acquire at the course level, and the figure on the right shows the average semester GPA that is used to assign financial aid at RSU.

ply. However, to do so, the administrators would have to know the student's full GPA and the GPA of their peers and be able to perfectly manipulate students near the threshold. Given the centralized nature of financial aid allocation and that students submit them electronically to the central administration and not within their departments, it is highly unlikely that administrators would be able to clearly manipulate the marginal student, as they would not know who the marginal student is. Evidence in support of this is also given by the balance test, as, if administrators selectively encouraged students to apply, I would expect discontinuities in student characteristics across the threshold.

One way to test for selection into treatment is through conducting a density test, wherein the distribution of grades just below and above the cutoff is compared (Cattaneo et al., 2020; McCrary, 2008). Although this test is useful for continuous data, the way that the GPA is constructed in my setting does not lend itself well to the density test. The aid is assigned using semester GPA, which is the average of the GPA of courses taken that semester. The policy is that the grade for a course can only be a whole number, which creates sharp discontinuities in the densities as shown in Figure 2.

Due to the structure of the data, a regular density test would be uninformative, as it would be picking up the discontinuities in the densities due to how the data is generated. At the same time, it is also possible that there are discontinuities in the densities and that

Figure 3: Distribution of Density Test Values for Stipends and Waivers



Note: These figures show the distribution of density test values for the dataset wherein the cutoff values are randomly reassigned within risk sets. Line indicates density test value for observed data.

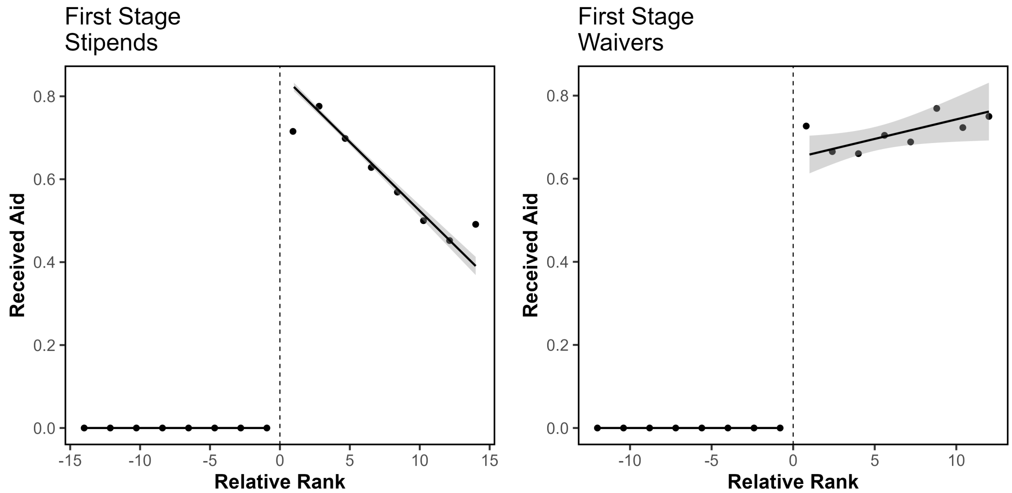
students are also selecting into treatment.

To estimate the probability of the density test failing due to the structure of the data, I use a permutation test. As the cutoff is set for each separate risk set at a specific value, I resample all of the cutoffs for the risk sets and reassign them to other risk sets. If students are selecting into treatment then the density test on the observed data should be a very extreme value. On the other hand, if the changes in densities are due to the structure of the data, then the observed values would not be extreme. I report the results of these tests in Figure 3.

Using the permutation approach, I fail to reject the null hypothesis that the observed value of the density test is different from a dataset where the cutoff is as good as random. Additionally, in section A in the appendix, I show that the distribution of grades for individual risk sets, as well as conduct a conditional density ratio test for the data to show that the conditional densities of student characteristics do not jump across the cutoff (Zimmerman, 2014). [3]

[3]The other side of the self-selection risk is the negative selection effect wherein students who might have performed better might decrease their performance if they know the precise cutoff. The competitive nature of the aid reduces this risk, as students cannot precisely predict where the cutoff will be as it is based on the number of available seats, applicants, and their grades. This means that a student who might be well above the cutoff would still be unable to safely reduce their performance, as they would not be able to know beforehand where the cutoff will be.

Figure 4: Change in Aid Receipt Probability for Stipends and Waivers



Note: These figures show the change in student probability of aid receipt based on rank distance from the individual with the smallest GPA to have received a given type of financial aid. The plotted points represent binned averages of the raw data, and the lines are linear fits to the raw data separately for each side of the cutoff.

It is important that the probability change of aid receipt at the threshold is significant. I plot the change in probability across the cutoff for both stipends and waivers in Figure 4. I find that the first stage for waivers is large and statistically significant, whereas the jump in aid receipt probability for stipends is smaller.

3.2 Estimating the Dynamic Treatment Effects of Aid

To understand the long-term consequences of aid, we must evaluate treatment effects beyond the immediate next semester. I employ local linear RD methods to estimate two fundamental parameters of the dynamic system. The total effect ($\delta^T_{t,t+k}$) represents the average causal effect for individuals near the cutoff of crossing the eligibility threshold in semester t on an outcome Y measured k semesters later ($Y_{i,t+k}$).

However, because the competition repeats each semester, eligibility at time t potentially improves a student's academic performance, thereby endogenously increasing their probability of eligibility in future semesters. Consequently, this total effect ($\delta^T_{t,t+k}$) is a combination of the direct marginal effect of semester t eligibility and indirect effects mediated through subsequent aid renewals.

This crowding-in parameter ($\pi_{t,t+k}$), which captures the average causal effect of crossing the threshold in semester t on the probability of crossing the threshold k semesters later, is estimated from:

$$Above_{i,j,t+k} = \alpha + \pi_{t,t+k} Above_{ijt} + g(r_{ijt}) + \theta_{jt} + \nu_{ijt} \tag{4}$$

where $g(r_{ijt})$ is a flexible polynomial function of rank and θ_{jt} represents risk set fixed effects.

Let $\delta^M_{t,t+k}$ denote the marginal effect - the average causal effect of eligibility in semester t on the outcome at $t+k$, holding eligibility status in all intermediate semesters constant. To formalize the decomposition of the total effect into its direct and indirect components, let h serve as an index for the intermediate periods, such that $1 \leq h \leq k$. The total impact operates not only through the immediate reception of aid, but also crowds in future aid, defined as:

$$\underbrace{\delta^T_{t,t+k}}_{\text{Total Effect}} = \underbrace{\delta^M_{t,t+k}}_{\text{Marginal Effect}} + \underbrace{\sum_{h=1}^{k} \left(\underbrace{\pi_{t,t+h}}_{\substack{\text{Effect on probability} \\ \text{of future eligibility}}} \times \underbrace{\delta^M_{t+h,t+k}}_{\substack{\text{Marginal Effect} \\ \text{in future semesters}}} \right)}_{\text{Crowding-in effect}} \tag{5}$$

To isolate the marginal effect ($\delta^M_{t,t+k}$), I employ methods from the dynamic RD literature to recursively decompose the impact (Biasi et al., 2024; Cellini et al., 2010; Taylor, 2014). This approach isolates the direct influence pathway from $Above_{ijt}$ to $Y_{i,t+k}$ by mathematically removing the estimated influence flowing through intermediate eligibility changes:

$$\underbrace{\delta^{M}_{t,t+k}}_{\text{Marginal Effect}} = \underbrace{\delta^{T}_{t,t+k}}_{\text{Total Effect}} - \underbrace{\sum_{h=1}^{k}\left(\underbrace{\pi_{t,t+h}}_{\substack{\text{Effect on probability}\\ \text{of future eligibility}}} \times \underbrace{\delta^{M}_{t+h,t+k}}_{\substack{\text{Marginal Effect}\\ \text{in future semesters}}}\right)}_{\text{Crowding-in effect}} \tag{6}$$

This recursive estimation requires a boundary condition. Because there are no intermediate periods to crowd in aid when a student is in their last semester, the marginal impact of aid eligibility equals the total impact of aid eligibility: $\delta^{M}_{t+k,t+k} = \delta^{T}_{t+k,t+k}$. This fact allows me to calculate the marginal effect of aid received at a student's final semester, which then allows me to calculate marginal effects of all previous aid.[4].

This recursive method constitutes my primary strategy for identifying the marginal impact of aid eligibility timing on both semester-level outcomes and final outcomes, such as graduation. It provides insights into the effectiveness of aid provision at different stages of a student's academic career, separate from its incentive effects on future aid receipt.

For implementation, the required δ^{T} and π components are estimated simultaneously via a system of equations using stacked regressions to obtain the full variance-covariance matrix of the component estimates. The marginal effects ($\delta^{M}_{t,t+k}$) are then computed recursively using Equation 6. Standard errors for the baseline recursive decomposition are

[4]In effect, this means estimating the marginal effect for each and every future semester, so, for 3 semesters out, the estimating equation becomes:

$$\begin{aligned}
\delta^{M}_{t,t+3} = \delta^{T}_{t,t+3} - \pi_{t,t+1} \times & \underbrace{\left(\delta^{T}_{t+1,t+3} - \pi_{t+1,t+2}[\delta^{T}_{t+2,t+3} - (\pi_{t+2,t+3} \times \delta^{T}_{t+3,t+3})] - (\pi_{t+1,t+3} \times \delta^{T}_{t+3,t+3})\right)}_{\delta^{M}_{t+1,t+3}} \\
- \pi_{t,t+2} \times & \underbrace{\left(\delta^{T}_{t+2,t+3} - (\pi_{t+2,t+3} \times \delta^{T}_{t+3,t+3})\right)}_{\delta^{M}_{t+2,t+3}} \\
- \pi_{t,t+3} \times & \underbrace{\left(\delta^{T}_{t+3,t+3}\right)}_{\delta^{M}_{t+3,t+3}}
\end{aligned}$$

calculated using a block bootstrap and, as an additional robustness test, using the Delta method.

To recursively isolate the marginal effect $\delta^M_{t,t+k}$, the estimator relies on a combination of several total effects estimators (δ^T and π) that are generated across different semesters, which requires three identifying assumptions. The first assumption is that for each δ^T and π estimand, the potential outcomes must be continuous at their respective cutoff. Second, because the eligibility cutoff changes dynamically from semester to semester, altering the sample composition of the marginal population, I assume that the local complier populations are sufficiently stable such that these dynamic parameters are homogenous across these changing risk sets. Third, the recursive estimator assumes additive separability - that the marginal impact of future aid is independent of a student's past aid history.

The institutional features support the first two assumptions. The first assumption of continuity of potential outcomes is similar to the continuity of potential outcomes discussed in the previous section and is supported by the same arguments. Regarding the second assumption, the primary threat to complier stability is that fluctuating cutoffs might capture systematically different types of marginal students over time. However, because students are locked into a fixed, pre-determined curriculum within their specific cohort, they are unable to strategically switch risk sets or alter course difficulty to game the shifting cutoffs. Consequently, the underlying complier pool remains structurally stable across periods.

However, the third assumption of additive separability could be potentially violated in my context. If dynamic complementarity is present, and aid is more effective for different types of students based on their previous performance, then the linear and additive approximation of the dynamic RD would be biased in approximating the isolated marginal effects of early aid. The direction of this bias can be signed based on the sign of the complementarity. If aid acts as a complement and past aid increases the effectiveness of future aid, then the average future marginal effects will understate the true indirect benefit for the students who were crowded into receiving that future aid and represent an upper bound estimate. Conversely, if aid acts as a substitute, proving more effective for individuals who never received past aid, the average future effects will overstate the true indirect benefit for these students. Subtracting this overstated indirect effect biases the resulting marginal effect downwards, representing a lower bound estimate.

4 Results: Total and Dynamic Impacts of Aid

4.1 The Total Impact of Financial Aid in a Competitive System

This section presents the overall impact of receiving financial aid (tuition waivers or stipends) on student effort and persistence throughout their studies, as estimated by a standard regression discontinuity design (Equation 1). These total effects (δ^T) reflect the consequences of awarding aid within the existing institutional framework, where aid is competitively reassigned each semester.

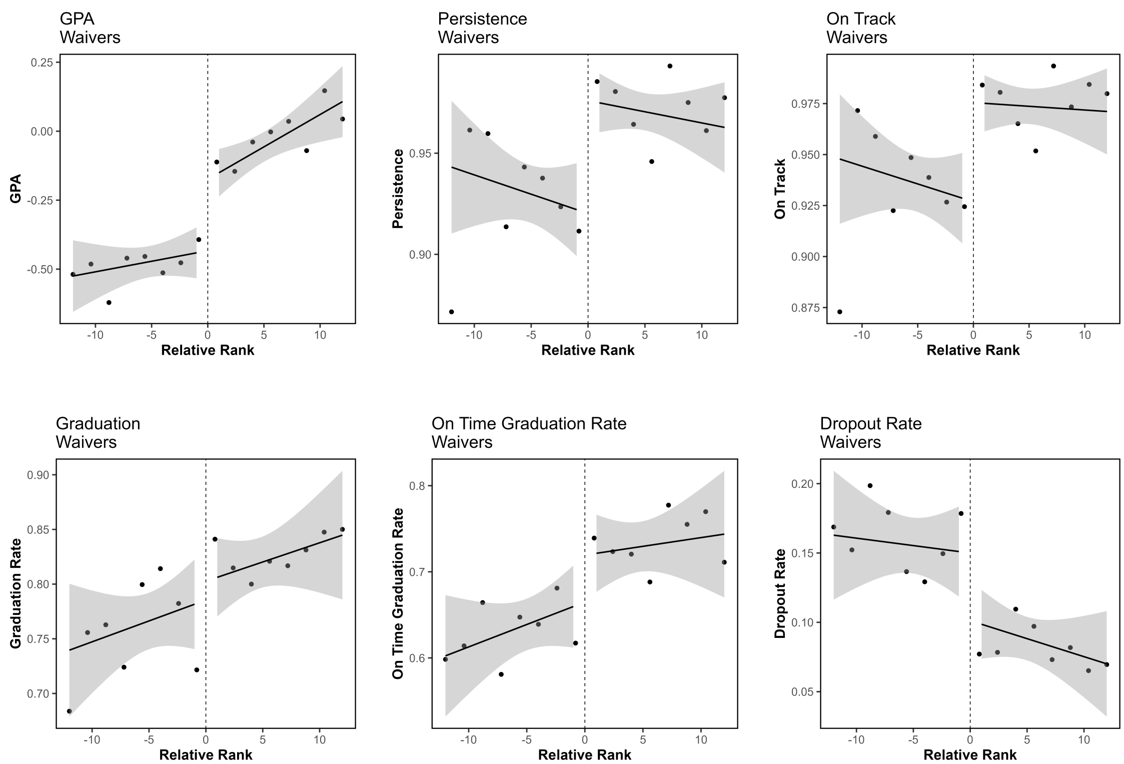
These estimates correspond to the impact of aid eligibility in a system where aid is competitively reassigned and answer the question of ”what is the impact of being eligible for financial aid, given that it will be reassigned later?”. These effects include both the marginal effects of aid eligibility, such as increased performance in the semester of aid reception, and the indirect effects of aid eligibility, such as increased probability of aid eligibility in future semesters, which in turn increases performance in future semesters, and so on.

4.1.1 Impact of Waiver Receipt

In this subsection, I analyze the effects of acquiring a waiver irrespective of previous and future history of reception of aid. This corresponds to the estimation of the treatment effects in equation 1 and provides estimates on the effect of acquiring a waiver for the next semester when the counterfactual is not acquiring it for the next semester. This is the margin under which many scholarships operate, as students have many opportunities for the acquisition of aid throughout their studies.

I now turn to estimating the impact of the reception of waivers. I first plot the impact of the provision of waivers in Figure 5, and report the results in Table 3.

Figure 5: Student Outcomes Below and Above the Tuition Waiver Reception Threshold



Note: These figures show the change in student outcomes based on distance from the rank cutoff for reception of tuition waivers. The plotted points are binned averages of the dependent variable, residualized by risk-set fixed effects. The lines are linear fits to the residualized data separately for each side of the cutoff.

I first estimate the Intent-to-Treat (ITT) effect of waiver eligibility, which captures the policy-relevant impact of crossing the threshold. I find that simply being eligible for a waiver significantly alters a student's academic trajectory. Specifically, waiver eligibility increases next-semester GPA by 0.378, boosts semester-to-semester persistence by 10.2 percentage points, increases the probability of being on track[5] by 8.9pp, raises the ultimate

[5]Being on track is defined as the student's semester number being the next number after their current

Table 3: Main Effects of Waivers on Outcomes

	OLS	Risk Set FE	2SLS	Per 1K EUR
GPA	0.336***	0.378***	0.410***	0.134***
	(0.099)	(0.091)	(0.098)	(0.039)
Persistence	0.109***	0.102***	0.130***	0.054***
	(0.022)	(0.022)	(0.021)	(0.009)
On Track	0.094***	0.089***	0.114***	0.047***
	(0.021)	(0.022)	(0.021)	(0.009)
Graduation	0.139**	0.124**	0.140***	0.060***
	(0.049)	(0.041)	(0.041)	(0.016)
Dropout	−0.128***	−0.115***	−0.144***	−0.060***
	(0.035)	(0.032)	(0.032)	(0.013)
On Time	0.171**	0.116*	0.153**	0.067***
	(0.054)	(0.050)	(0.049)	(0.019)
Risk Set FE		X	X	X
Num.Obs.	1864	1864	1864	1598

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

Note:

Note: The table reports intent-to-treat (OLS and Risk Set FE) and instrumental variable (2SLS) estimates of the effect of waivers eligibility on student outcomes. OLS estimates are from a local linear regression of the outcome on the eligibility indicator. Risk Set FE includes risk set fixed effects. 2SLS estimates instrument actual waivers receipt with eligibility. Per 1K EUR estimates instrument the monetary value of the waivers (in thousands of Euros) with eligibility. Persistence is defined as an indicator for whether the student is enrolled in the university in the following semester. On Track is defined as an indicator for whether the student progresses to the next academic semester in the following term (e.g. from semester 1 to semester 2). All models except OLS include risk set fixed effects, and all models cluster standard errors at the student level in parentheses. The minimum, maximum, and average first-stage F-statistics across the 2SLS models are 649.6, 796.6, and 742.2 respectively.

graduation rate by 12.4 percentage points, and decreases the probability of dropping out by 11.5 percentage points.

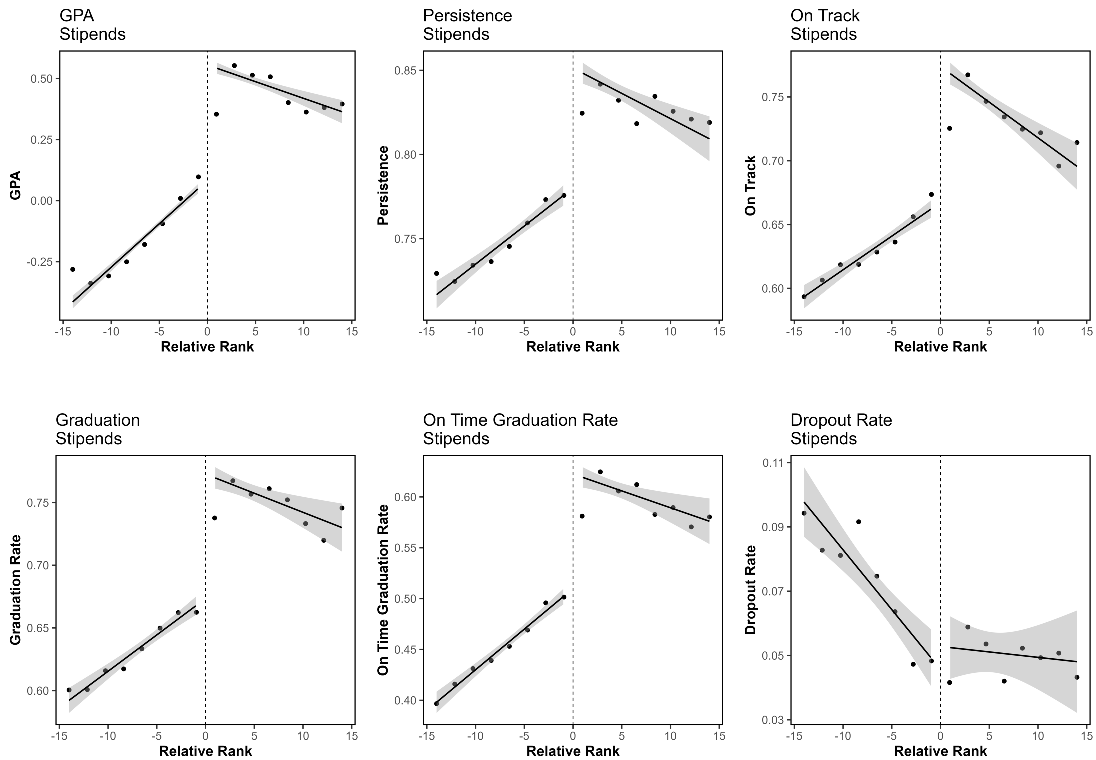
When instrumenting for actual waiver receipt via 2SLS, the estimates grow substantially - for instance, the impact on graduation rises to 14 percentage points. While these estimates reside at the upper bound of the broader financial aid literature, they reflect the unique, compounding incentive structure of this specific tournament. Holding a tuition waiver is a strict institutional precondition for competing for a stipend. Consequently, the large 2SLS estimates capture not merely the financial relief of waived tuition, but the powerful option value of gaining entry into the subsequent stipend tournament.

4.1.2 The Impact of Stipend Receipt

Figure 6 provides a graphical representation of the changes in student outcomes across the threshold for the combined sample. The plots show the changes in outcomes based on the student's rank distance from the marginal peer who received aid in their respective risk set.

semester. In Latvia, as in many countries in Europe, students choose to study in specific programs upon enrolment, which have a pre-defined course and semester sequence.

Figure 6: Student Outcomes Below and Above the Stipend Reception Threshold



Note: These figures show the change in student outcomes based on distance from the rank cutoff for the reception of stipends across both institutions. The plotted points are binned averages of the dependent variable, residualized by risk-set fixed effects. The lines are linear fits to the residualized data separately for each side of the cutoff. Dropout is omitted as it is only tracked in the RSU subset.

Table 4 reports the regression estimates of the impact of aid receipt on academic outcomes. By instrumenting actual stipend receipt with cutoff eligibility, I find that stipends have a powerful effect on student effort and academic progression.

I find that receiving a stipend yields substantial academic returns across both the intensive and extensive margins. Specifically, the 2SLS estimates show that stipend receipt increases a student's next-semester GPA by 0.276. Beyond just eliciting greater academic effort, stipends meaningfully improve academic progression: they increase semester-to-semester persistence by 6.1 percentage points, the probability of remaining on track by 7.8 percentage points, and the ultimate graduation rate by 7.9 percentage points.

Table 4: Main Effects of Stipends on Outcomes

	OLS	Risk Set FE	2SLS	Per 1K EUR
GPA	0.231***	0.214***	0.276***	0.545***
	(0.019)	(0.019)	(0.022)	(0.043)
Persistence	0.112***	0.045***	0.061***	0.118***
	(0.008)	(0.006)	(0.006)	(0.012)
On Track	0.164***	0.061***	0.078***	0.149***
	(0.009)	(0.008)	(0.009)	(0.017)
Graduation	0.154***	0.066***	0.079***	0.155***
	(0.010)	(0.008)	(0.009)	(0.017)
Dropout	−0.028**	0.007	−0.011	−0.021
	(0.010)	(0.009)	(0.013)	(0.024)
On Time	0.162***	0.067***	0.082***	0.160***
	(0.010)	(0.009)	(0.010)	(0.019)
Risk Set FE		X	X	X
Num.Obs.	39 979	39 978	39 978	39 978

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

Note:

Note: The table reports intent-to-treat (OLS and Risk Set FE) and instrumental variable (2SLS) estimates of the effect of stipends eligibility on student outcomes. OLS estimates are from a local linear regression of the outcome on the eligibility indicator. Risk Set FE includes risk set fixed effects. 2SLS estimates instrument actual stipends receipt with eligibility. Per 1K EUR estimates instrument the monetary value of the stipends (in thousands of Euros) with eligibility. Persistence is defined as an indicator for whether the student is enrolled in the university in the following semester. On Track is defined as an indicator for whether the student progresses to the next academic semester in the following term (e.g. from semester 1 to semester 2). All models except OLS include risk set fixed effects, and all models cluster standard errors at the student level in parentheses. The minimum, maximum, and average first-stage F-statistics across the 2SLS models are 2914.7, 35545.8, and 27737.1 respectively.

The economic magnitude of these effects highlights the power of the tournament design. By scaling these estimates to the per-€1,000 level, it becomes clear that providing even relatively modest, liquid financial support through a competitive mechanism effectively elicits effort across the broad student population. This is consistent with a framework where stipends alleviate immediate liquidity constraints, allowing students to substitute away from part-time work and reallocate that time toward their studies. While these pooled estimates effectively capture the generalized mechanism of the tournament, the baseline effects do vary slightly depending on the specific institution. How these effects differ by institution is detailed in Appendix D.

4.1.3 Do the Effects Differ for Different Types of Students?

An essential question for further exploration of the effects of financial aid in the context of efficient program design is who is most impacted by it. I would expect to find that the individuals that most benefit from aid are those that have higher opportunity costs, as well as at lower levels of academic achievement and earlier in their studies. The reasoning behind this is that students at those margins are more credit-constrained and are thus more receptive to additional aid. Furthermore, given the compounding nature of aid, it is also likely that the earlier a student is provided financial aid, the more time the effect of aid has to compound.

The sequenced nature of aid, where the cutoff percentile changes from semester to semester, creates additional opportunities to investigate heterogeneities based on various financial aid program design characteristics and the characteristics of recipients. To explore these questions, I run further analysis by demographics, adding interaction terms with being above the cutoff in my regressions with various student demographics and characteristics of the provision of aid itself, such as its timing and the percentile at which the cutoff occurred. Table 5 reports the estimates for the heterogeneity of effects by student demographics.

Table 5: Heterogeneity by Demographics in the Effects of Aid on Student Outcomes

	Heterogeneity Variable			
Outcome	Male	Age	Minority	Capital
Stipends				
GPA	-0.095+	-0.001	-0.003	-0.002
	(0.050)	(0.004)	(0.057)	(0.039)
Persistence	0.018	0.001	0.019	0.031**
	(0.015)	(0.001)	(0.017)	(0.012)
On Track	0.021	0.001	0.035	0.033*
	(0.020)	(0.001)	(0.024)	(0.016)
Dropout	0.031	-0.001	-0.039	-0.012
	(0.033)	(0.002)	(0.029)	(0.018)
Graduation	-0.011	0.002	0.028	0.013
	(0.020)	(0.002)	(0.024)	(0.016)
Ontime	-0.003	-0.001	0.056*	0.024
	(0.022)	(0.002)	(0.027)	(0.018)
Risk Set FE	X	X	X	X
Num.Obs.	39243	38895	38130	38130
Waivers				
GPA	-0.013	0.008	-0.277	0.016
	(0.291)	(0.015)	(0.283)	(0.184)
Persistence	-0.076	0.005	0.064	0.001
	(0.061)	(0.004)	(0.072)	(0.047)
On Track	-0.066	0.005	0.062	0.004
	(0.061)	(0.004)	(0.072)	(0.045)
Dropout	0.108	0.002	-0.040	0.050
	(0.083)	(0.005)	(0.088)	(0.064)
Graduation	0.003	-0.004	0.034	-0.015
	(0.108)	(0.006)	(0.097)	(0.080)
Ontime	0.024	-0.007	-0.004	0.024
	(0.128)	(0.006)	(0.147)	(0.093)
Risk Set FE	X	X	X	X
Num.Obs.	1864	1827	1827	1827

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

[a] The table reports heterogeneity analysis by student demographics. The coefficients reflect the interaction between aid eligibility and the respective demographic indicator. All models include risk set fixed effects. Robust standard errors clustered at the student level.

What I find is that generally the aid effectiveness does not vary by student demographics, with some slightly larger impacts on persistence and progression for students from the capital, but only for stipends.

4.1.4 The Impact of Providing Aid as a Tournament

The way a competition is designed can both help and hurt student performance. On the positive side, tournaments motivate students in two main ways. First, winning increases the chance of winning again in the future, giving students a long-term reason to try hard. Second, these tournaments are especially good at pushing the highest-performing students to work even harder. However, there is a downside. If students feel they have no chance of winning - for instance, if awards are only given to a tiny percentage of participants - they can become discouraged and perform worse.

I estimate the impacts of financial aid by the characteristics of the risk set, at which percentile within the risk set the cutoff occurs, as well as how late throughout one's studies. Table 6 reports the results.

I explore the option value of financial aid as described by the literature on performance tournaments by looking at the impact of financial aid at the end of one's studies when there is no future option for renewal. I find that there are considerably stronger effects on persistence for students in the first half[6] of their studies, with students in the first half receiving stipends having increased probability of persistence by 2.5pp, but lower impact on GPA by 0.14σ. Similarly, students receiving waivers in the last year have smaller impacts on persistence and probability of being on track, and students receiving waivers in their last semesters seeing smaller impacts on their dropout and graduation rates.

Exploring heterogeneity by cutoff characteristics, I find evidence that financial aid is more effective at lower percentiles. For waivers, moving from the bottom to the top percentile of the cutoff decreases the impact on persistence by 30.8 percentage points and

[6]The reason that the first half is used rather than semesters is due to the fact that the university has very different program lengths, from 6-year programs for medical professionals to 2-year master's degrees

Table 6: Heterogeneity by Cutoff Characteristics in the Effects of Aid on Student Outcomes

	Heterogeneity Variable				
Outcome	Cutoff Percentile	First Year	First Half	Last Year	Last Semester
Stipends					
GPA	-0.189+	-0.154***	-0.143***	0.050	0.055
	(0.103)	(0.039)	(0.037)	(0.037)	(0.044)
Persistence	-0.048	0.035**	0.025*	0.003	0.006
	(0.031)	(0.013)	(0.011)	(0.012)	(0.014)
On Track	-0.041	0.017	0.014	0.013	0.040*
	(0.035)	(0.015)	(0.015)	(0.015)	(0.019)
Dropout	0.048	-0.002	-0.013	-0.016	0.021
	(0.040)	(0.023)	(0.016)	(0.017)	(0.020)
Graduation	-0.069+	0.014	0.013	0.021	0.031
	(0.040)	(0.017)	(0.015)	(0.015)	(0.019)
Ontime	-0.067	-0.001	0.016	0.016	0.025
	(0.042)	(0.017)	(0.016)	(0.016)	(0.021)
Risk Set FE	X	X	X	X	X
Num.Obs.	39979	39979	39946	39946	39946
Waivers					
GPA	-0.498	0.258	0.091	0.146	0.272
	(0.378)	(0.182)	(0.190)	(0.182)	(0.304)
Persistence	-0.308**	0.002	0.075+	-0.152***	0.004
	(0.095)	(0.047)	(0.040)	(0.040)	(0.059)
On Track	-0.312***	0.016	0.066+	-0.129***	-0.004
	(0.091)	(0.046)	(0.040)	(0.039)	(0.063)
Dropout	0.109	-0.025	-0.127*	0.064	0.139*
	(0.131)	(0.070)	(0.057)	(0.063)	(0.059)
Graduation	-0.230	0.017	0.199*	0.065	-0.304***
	(0.181)	(0.093)	(0.079)	(0.082)	(0.086)
Ontime	-0.275	-0.074	0.048	0.043	-0.142
	(0.218)	(0.115)	(0.097)	(0.112)	(0.133)
Risk Set FE	X	X	X	X	X
Num.Obs.	1864	1864	1864	1864	1864

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

Note: The table reports combined heterogeneity analysis by characteristics of the cutoff itself. Each column reports the coefficient on the interaction term between eligibility and the characteristic. Cutoff Percentile is the percentile rank of the cutoff within the risk set. First Half indicates if the student is in the first half of their program. All models include risk set fixed effects. Robust standard errors clustered at the student level.

the probability of being on track by 31.2 percentage points. This implies that financial aid tournaments are more effective when the number of awards relative to the number of participants is larger, which would align with the theoretical predictions of individuals being incentivized by tournaments more if they believe that they have higher chances of winning.

I also explore the risk versus security effects of financial aid. The impact of the tournament can also vary by the intensity of competition. To estimate the impact of increased levels of competition and risk, I leverage several sources of variation.

First, I leverage the fact that waivers, if provided starting in the fall semester, are provided for the whole academic year or two semesters. Meaning that individuals who receive financial aid in the fall should feel less of a competitive effect in the first semester, as they have secured financial aid for the next semester irrespective of their performance.

Second, I explore heterogeneity by the level of difficulty of the risk set. To do so, I use two different measures of difficulty - average GPA and average rate of being on track after the semester. Finally, I also leverage the fact that individuals who begin their studies with a tuition waiver have the waiver guaranteed for the rest of their studies. Thus, they are less at risk of losing both types of financial aid. I explore heterogeneity for the impact of stipends for this group. I report the results in Table 7.

Generally, financial aid appears to be most effective for individuals who are struggling, with security effects increasing persistence, but decreasing student effort. Waivers exhibit strong compensatory effects in higher-difficulty cohorts: below-median GPA risk sets see a 0.35σ larger impact on next-semester GPA and an 8.9pp increase in persistence. Similarly, below-median progression cohorts see a 0.493σ GPA boost, alongside 26pp and 24.6pp increases in persistence and on-track probability, respectively. Stipends reinforce this compensatory pattern on the extensive margin; in below-median progression cohorts, stipends increase persistence by 4.9pp, on-track probability by 6.8pp, and ultimate graduation by 6.8pp. Furthermore, structural security significantly alters the behavioral re-

Table 7: Heterogeneity by Competitiveness in the Effects of Aid on Student Outcomes

	Heterogeneity Variable			
Outcome	Fall (RSU)	<Median GPA	<Median Progression	Guaranteed Aid (RSU)
Stipends				
GPA	-0.030	0.005	0.037	-0.292*
	(0.053)	(0.038)	(0.039)	(0.129)
Persistence	-0.012	0.009	0.049***	0.004
	(0.008)	(0.012)	(0.010)	(0.014)
On Track	-0.012	-0.012	0.068***	0.003
	(0.008)	(0.015)	(0.013)	(0.014)
Dropout	-0.003	0.028	-0.109	-0.023
	(0.014)	(0.018)	(0.130)	(0.037)
Graduation	0.019	-0.001	0.068***	-0.002
	(0.017)	(0.015)	(0.015)	(0.057)
Ontime	0.027	-0.014	0.035*	0.004
	(0.024)	(0.017)	(0.017)	(0.073)
Risk Set FE	X	X	X	X
Num.Obs.	16360	39979	39979	16360
Waivers				
GPA	0.145	0.350+	0.493**	
	(0.196)	(0.184)	(0.183)	
Persistence	-0.090+	0.089*	0.260***	
	(0.051)	(0.044)	(0.055)	
On Track	-0.063	0.076+	0.246***	
	(0.048)	(0.043)	(0.055)	
Dropout	0.053	-0.049	-0.147*	
	(0.072)	(0.057)	(0.065)	
Graduation	-0.069	0.049	0.098	
	(0.082)	(0.070)	(0.089)	
Ontime	-0.006	-0.037	0.143	
	(0.107)	(0.088)	(0.110)	
Risk Set FE	X	X	X	
Num.Obs.	1864	1864	1864	

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

[a] The table reports combined heterogeneity analysis by various measures of competitiveness. Each column reports the coefficient on the interaction term between eligibility and the column variable. Fall (RSU) indicates Fall semester, estimated only for RSU students who receive a waiver in the Fall for two semesters. <Median GPA and <Median Progression indicate higher difficulty risk sets. Guaranteed Aid (RSU) indicates students who started with a waiver, also estimated only for RSU, as students who start with a guaranteed waiver are guaranteed it throughout their studies. All models include risk set fixed effects. Robust standard errors clustered at the student level.

sponse to stipends. For students with the absolute security of a guaranteed tuition waiver, this safety net actually induces a complacency effect, with decreased impacts on academic effort (GPA) by 0.29σ.

I also explore institution-specific heterogeneity in Appendix D. I find a consistent life-cycle of aid across both institutions: early stipends act primarily as a retention mechanism to reduce dropout, with diminishing effects later on. Furthermore, in settings where many competitors already possess the safety net of a guaranteed tuition waiver (such as RSU), the marginal impact of a stipend is heavily concentrated on increasing student effort (as measured by GPA), whereas in higher-stakes environments without guaranteed waivers (such as UL), stipends drive increases in ultimate persistence and graduation.

4.2 Decomposing Dynamic Treatment Effects: Marginal Impacts, Crowd-In, and Optimal Timing

The previous section established the total impact of financial aid in a system where aid is reallocated based on ongoing performance. However, these total effects amalgamate the immediate, direct impact of receiving aid in a given semester with the indirect impact that arises because aid receipt can improve performance and thus increase the probability of receiving aid in subsequent semesters (a crowding-in effect). This section aims to disentangle these components using the dynamic regression discontinuity framework.

Specifically, I first examine the extent to which current aid receipt affects future aid probability ($\pi_{t,t+h}$). I then isolate the marginal impact of a single aid instance ($\delta^M_{t,t+k}$), holding future aid receipt constant. Finally, I investigate how the timing of aid (early vs. late in a student's academic career) affects long-term outcomes like graduation.

4.2.1 The Crowding-In Effect of Aid

I conduct further analysis to evaluate the effects of being offered aid on student outcomes in subsequent semesters. I use lagged values of the dependent variables to explore the impact of the provision of aid in future semesters and report them in Table 8

I generally find that being eligible for either type of aid has considerable crowding-in effects on future aid. Being eligible for a waiver increases their probability of receiving a waiver for up to five semesters ahead, increasing their probability of receiving a waiver in five semesters by 14.6pp, and crowding in additional aid amounts. This effect is driven by individuals persisting through their studies, as being eligible for waiver increases persistence by 6.2pp after five semesters.

Similarly, stipend receipt also crowds in additional stipends, with individuals after five semesters being 5.1pp more likely to hold a stipend. This effect, however, seems to be driven primarily by student effort, as stipend receipt increases future student GPA.

4.2.2 Intertemporal Impact of Aid: Early vs. Late Aid on Graduation

In this subsection, I explore whether the marginal impact of aid on long-term success, specifically graduation, differs depending on when it is received in a student's academic trajectory (e.g. early vs. late). I estimate the marginal impact of aid for different semesters.

To estimate the marginal impact of aid in any given semester, I first subset the data to take students who were undergraduates and who had a program length of 8 semesters (the most popular program length for undergraduate study), and who started and whose expected graduation falls within the timeframe of the data.

The goal of this subsetting is to ensure that the estimates are from individuals who are observed throughout the time period that I have data for and who have the same program length, to ensure that effects are not driven by attrition at the program level. In this section I report the estimates for waivers due to their impact, the results for stipends are available in the appendix. I report my estimates in Figure 7

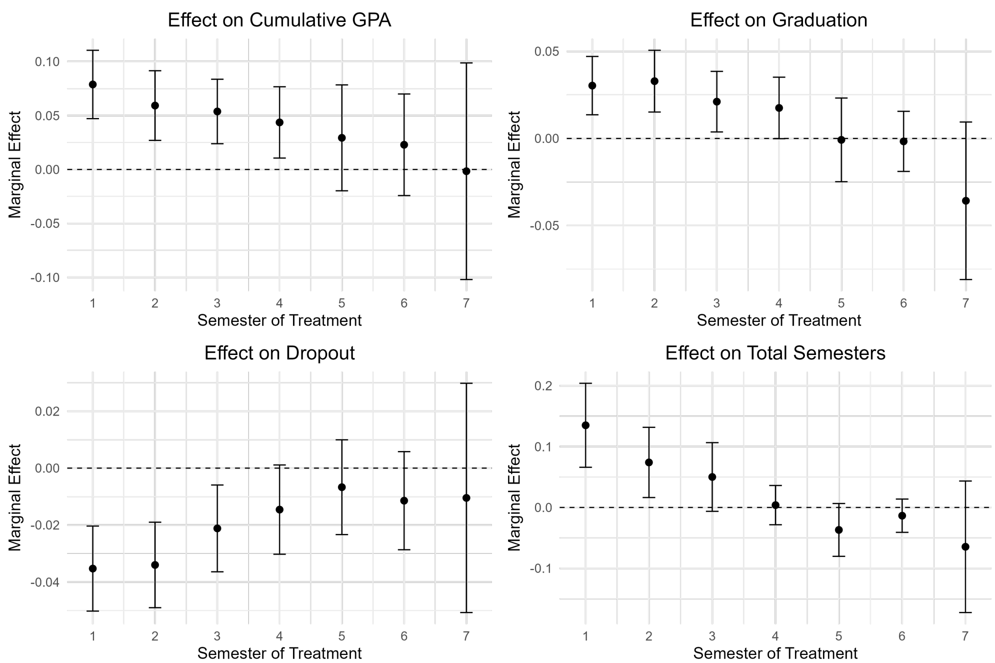
Table 8: Effects Over Time

	GPA	Persistence	On Track	Aid	Aid in 000s of EUR
Stipends					
Next Semester	0.175***	0.002	0.003	0.557***	0.302***
	(0.028)	(0.004)	(0.004)	(0.010)	(0.006)
2 semesters out	0.176***	0.001	0.009	0.119***	0.073***
	(0.033)	(0.006)	(0.006)	(0.011)	(0.006)
3 semesters out	0.096*	-0.017**	0.001	0.064***	0.037***
	(0.038)	(0.006)	(0.007)	(0.012)	(0.007)
4 semesters out	0.070	-0.012*	0.001	0.053***	0.029***
	(0.048)	(0.006)	(0.008)	(0.013)	(0.008)
5 semesters out	0.086	0.004	0.006	0.051**	0.031**
	(0.054)	(0.005)	(0.008)	(0.016)	(0.010)
6 semesters out	0.147*	-0.003	0.004	0.032+	0.014
	(0.068)	(0.005)	(0.008)	(0.018)	(0.011)
Risk Set FE	X	X	X	X	X
Num.Obs.	14932	16360	16212	16360	16360
Waivers					
Next Semester	0.378***	0.102***	0.089***	0.769***	2.109***
	(0.091)	(0.022)	(0.022)	(0.023)	(0.067)
2 semesters out	0.344**	0.106***	0.147***	0.434***	1.335***
	(0.109)	(0.025)	(0.031)	(0.033)	(0.099)
3 semesters out	0.048	0.056*	0.151***	0.113**	0.340**
	(0.147)	(0.027)	(0.032)	(0.038)	(0.117)
4 semesters out	0.296+	0.085***	0.170***	0.125*	0.324*
	(0.155)	(0.026)	(0.033)	(0.052)	(0.140)
5 semesters out	0.032	0.062**	0.124***	0.146**	0.388**
	(0.229)	(0.022)	(0.030)	(0.055)	(0.148)
6 semesters out	-0.059	0.014	0.114***	0.044	0.133
	(0.221)	(0.022)	(0.030)	(0.077)	(0.206)
Risk Set FE	X	X	X	X	X
Num.Obs.	1660	1864	1863	1864	1598

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

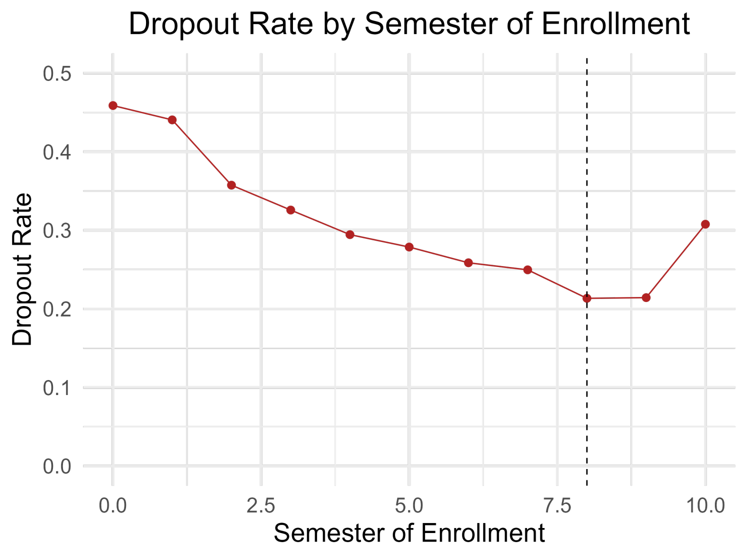
Note: The table reports reduced-form estimates of aid eligibility on outcomes in subsequent semesters (t+1 to t+6). Each cell represents a separate regression including risk set fixed effects. Persistence is defined as an indicator for whether the student is enrolled in the university in the given semester. On Track is defined as an indicator for whether the student has progressed to the expected academic semester for that term. Robust standard errors clustered at the student level in parentheses.

Figure 7: Marginal Effect of Waiver Eligibility at a Given Semester



Note: The figures report the estimates from an indirect regression discontinuity decomposition on the marginal impact of being eligible for waivers and total received aid in any given semester on a range of student outcomes - cumulative GPA, graduation, ever dropping out, and the total number of semesters that a student is enrolled for. The estimation is done on students who start during the time period and whose expected graduation falls before the data horizon, and whose program length is 8 semesters. Standard errors acquired by conducting a cluster bootstrap.

Figure 8: Probability of Dropping out by Semester for Undergraduates With a Program Duration of 4 years



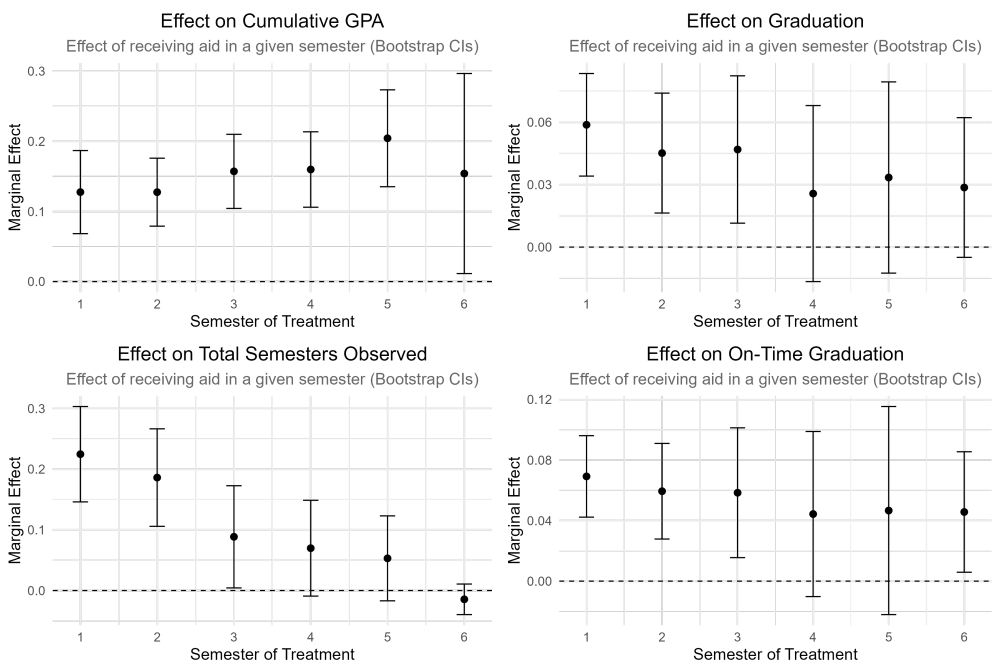
Note: This figure reports the probability that an individual observed in a given semester would drop out at any future time for a subset of individuals who are studying in 4-year undergraduate programs. Dashed line indicates semester 8 - the final semester in one's studies for this subgroup.

I find that the impact of waiver eligibility is higher in earlier semesters for most, with the effect only being statistically significant in the first year or first two semesters for increasing graduation and decreasing dropout.

The reason for this can also be found in the setting. In Figure 8 I plot the probability of ever dropping out by individuals in each semester. This plots the probability of ever dropping out of the program for all individuals who have been observed in that semester. What I find is that the probability of dropping out is highest in the first semesters, after which it decreases, only jumping again at the final semester.

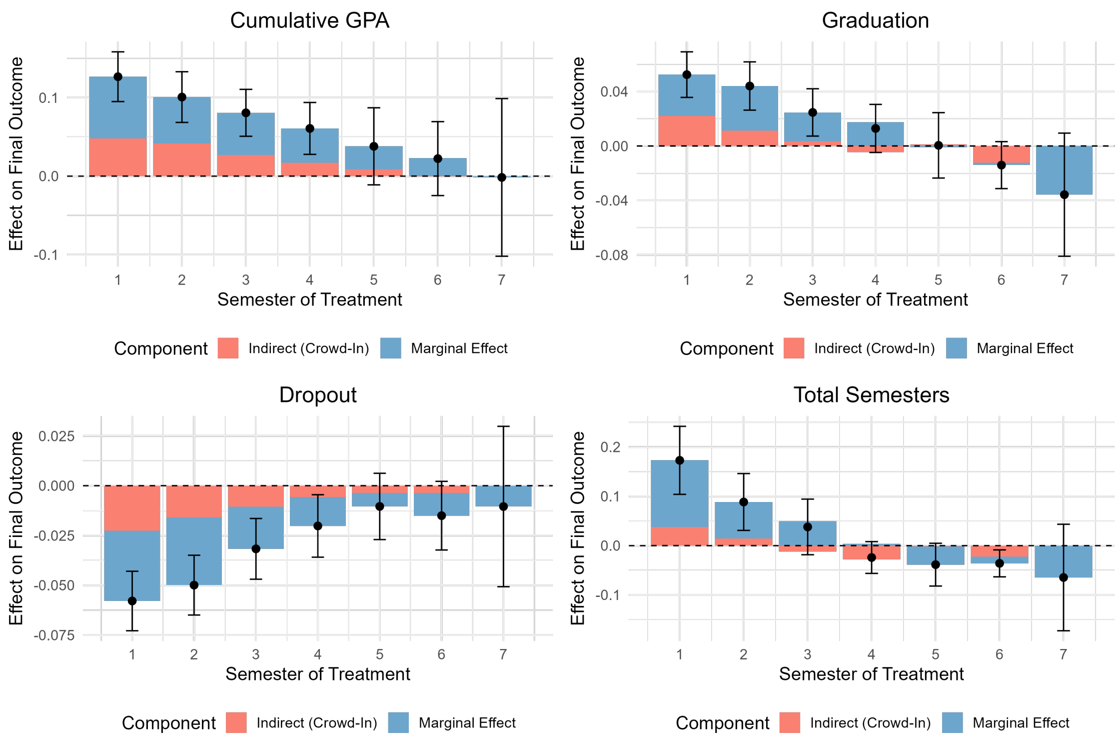
Additionally, I take the subset of individuals who were studying in 6-semester-long undergraduate programs (the most popular choice among students in the stipend sample), and conduct a decomposition into the marginal and indirect effects (Figure 9. I find a similar pattern with the impact of aid on student persistence being highest in the earlier semesters, with the effect decreasing the second half of one's studies. At the same time, however, the impact on cumulative GPA stays strong throughout one's studies.

Figure 9: Marginal Effect of Stipend Eligibility at a Given Semester



Note: The figures report the estimates from an indirect regression discontinuity decomposition on the marginal impact of being eligible for stipends in any given semester on a range of student outcomes. The estimation is done on students who start during the time period and whose expected graduation falls before the data horizon, and whose program length is 6 semesters.

Figure 10: Decomposition of Impact of Waiver Eligibility



Note: The figures report the estimates from an indirect regression discontinuity decomposition on the marginal, indirect, and total impact of being eligible for waivers in any given semester on a range of student outcomes. The estimation is done on students who start during the time period and whose expected graduation falls before the data horizon, and whose program length is 8 semesters. Standard errors acquired using the delta method.

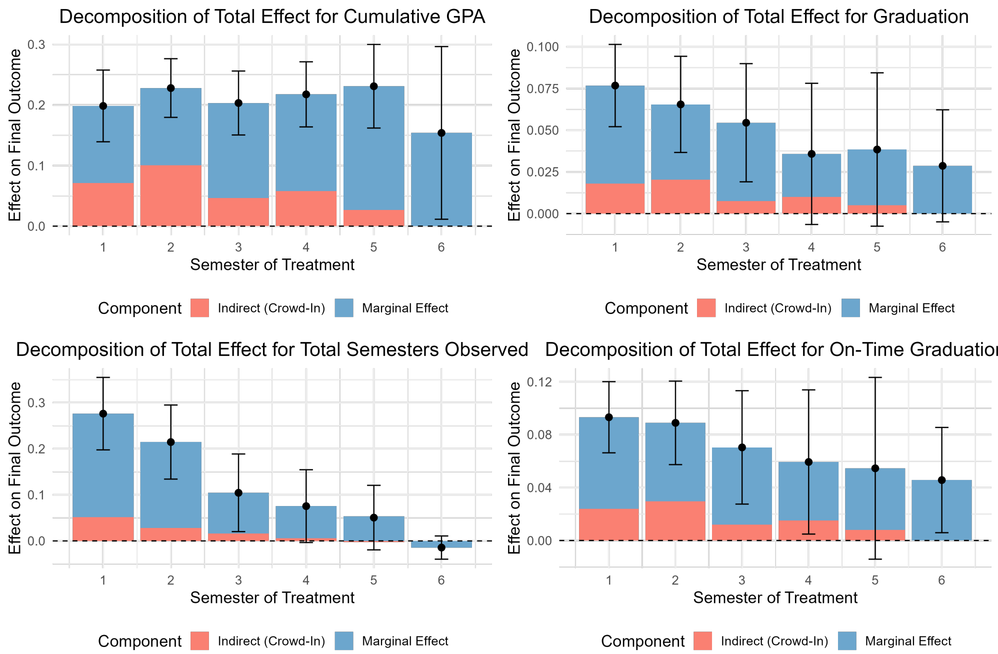
4.2.3 Marginal Effect of Aid vs Crowding-In

I now turn to decomposing the total effect in every semester into the marginal effect (driven by aid eligibility in a given time) and the indirect effect (driven by future aid eligibility). I thus decompose the results for waivers in Figure 7 into the total, marginal, and crowding in effects in Figure 10 based on equation 6

Decomposing the effects into the marginal and crowd-in for stipends (Figure 11), I find that the marginal effect plays a larger role compared to the crowd-in effect for earlier semesters for stipends. However, the crowd-in effect is most pronounced in the earliest semesters and decreasing over time.

Generally, what I find is that the considerable impact of aid in earlier semesters is affected by their crowding-in effect of future aid. Furthermore, the crowding-in effect is

Figure 11: Decomposition of Impact of Stipend Eligibility



Note: The figures report the estimates from an indirect regression discontinuity decomposition on the marginal, indirect, and total impact of being eligible for stipends in any given semester on a range of student outcomes. The estimation is done on students who start during the time period and whose expected graduation falls before the data horizon, and whose program length is 6 semesters. Standard errors estimated through cluster bootstrap.

strongest in the first semesters, after which it dissipates.

4.3 Dynamic Complementarities in Financial Aid

The unique mechanism of aid allocation also allows further exploration of treatment effect heterogeneity of financial aid based on students' previous stock of skills. Based on the framework by Cunha and Heckman (2007), individual investments in human capital are more effective for individuals with higher a priori levels of human capital, as they are able to produce additional human capital more efficiently, creating dynamic complementarity in investment.

To explore these mechanisms, I assume GPA as a proxy for human capital and use a two-stage least squares approach, wherein I estimate the following equation:

$$CGPA_{i,t+1,j} = \beta_0 + \beta_1 CGPA_{itj} + \beta_2 Aid_{itj} + \beta_3 (CGPA_{itj} \times Aid_{itj}) + f(r_{itj}) + \theta_{tj} + \epsilon_{it} \quad (7)$$

Which is equation 1 with an additional interaction of aid and previous CGPA. And I instrument Aid_{itj} and $(CGPA_{itj} \times Aid_{itj})$ using the following equations:

$$\begin{aligned} Aid_{itj} &= \pi_{10} + \pi_{11} Above_{itj} + \pi_{12}(CGPA_{itj} \times Above_{itj}) \\ &\quad + \pi_{13} CGPA_{itj} + f(r_{itj}) + \theta_{tj} + v_{1it} \end{aligned} \quad (8)$$

$$\begin{aligned} (CGPA_{itj} \times Aid_{itj}) &= \pi_{20} + \pi_{21} Above_{itj} + \pi_{22}(CGPA_{itj} \times Above_{itj}) \\ &\quad + \pi_{23} CGPA_{itj} + f(r_{itj}) + \theta_{tj} + v_{2it} \end{aligned} \quad (9)$$

This approach allows me to use the plausibly exogenous variation caused by the jump in aid receipt probability upon crossing the threshold to partial out the impact of aid specifically for individuals with different previous levels of human capital. The coefficient on β_3 in the second stage equation would capture the effects of dynamic complementarity in skills and provide evidence on whether the investments in the skills of individuals are more effective for individuals with higher skills a prior. I report the results in Table 9 for waivers and stipends on next-semester CGPA.

Contrary to a pure dynamic complementarity framework, I find mixed and margin-specific results. The interaction between prior human capital and financial aid depends fundamentally on whether we examine short-term academic effort (the intensive margin) or ultimate degree attainment (the extensive margin). For short-term academic effort, there is suggestive evidence of dynamic complementarity. Table 9 shows that the interaction between a student's current CGPA and stipend receipt on next-semester GPA is positive (0.059σ). This indicates that for already high-achieving students, winning a tournament prize can act as an effort multiplier. However, this effect does not uniformly hold across all margins, as cumulative past aid shows a slightly compensatory effect (-0.035σ).

When evaluating long-term extensive margins, however, aid acts in a strictly compensatory manner. Table 10 demonstrates that the interaction between aid and prior human capital (current CGPA) is strongly negative for degree attainment. The interaction of stipend receipt with current CGPA on graduation is -0.038, and with cumulative past aid is -0.040. Waivers exhibit an even stronger compensatory interaction with current CGPA (-0.125).[7]

Rather than simply compounding the success of the already-resourced, financial aid is also effective at helping marginal, struggling students cross the finish line. Thus, while the tournament may multiply the effort of top performers in the short term, its ultimate extensive-margin value lies in alleviating the binding constraints of those with lower a priori human capital.

Furthermore, these estimates provide evidence of the violation of the assumption of additive separability in the dynamic RD design. Because aid exhibits positive dynamic complementarity for cumulative GPA (acting as an effort multiplier), the average future

[7] These compensatory effects on extensive margins are particularly pronounced in high-stakes environments without guaranteed safety nets, such as is the case in UL. A detailed breakdown of dynamic complementarity by specific institution is provided in Appendix D.

Table 9: Dynamic Complementarity: Effects on Next Semester GPA

	Current CGPA	Cum. Past Aid	Past Aid	Math HS (UL)
Stipends				
Aid Receipt	0.044	0.241***	0.265***	0.152
	(0.028)	(0.024)	(0.033)	(0.116)
Aid * Current CGPA	0.059*			
	(0.025)			
Aid * Cum. Past Aid		-0.035*		
		(0.016)		
Aid * Past Aid (Lag)			0.016	
			(0.038)	
Aid * Math HS (UL)				0.001
				(0.001)
Risk Set FE	X	X	X	X
Num.Obs.	29582	29582	20362	6865
Waivers				
Aid Receipt	0.287**	0.463***	0.301*	
	(0.100)	(0.108)	(0.127)	
Aid * Current CGPA	0.027			
	(0.082)			
Aid * Cum. Past Aid		-0.228+		
		(0.134)		
Aid * Past Aid (Lag)			0.009	
			(0.206)	
Risk Set FE	X	X	X	
Num.Obs.	1503	1503	1147	

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

Note:

Results from two-stage least squares regressions estimating the impact of current aid receipt on next-semester GPA. The endogenous interactions test for dynamic complementarities across proxies of skill and resources for both stipends and waivers. All models include risk set fixed effects and control for the running variable. Robust standard errors clustered at the student level.

Table 10: Dynamic Complementarity: Effects on Graduation

	Current CGPA	Cum. Past Aid	Past Aid	Math HS (UL)
Stipends				
Aid Receipt	0.076***	0.100***	0.069***	0.088
	(0.011)	(0.010)	(0.012)	(0.055)
Aid $\times CurrentCGPA$	-0.042***			
	(0.010)			
Aid $\times Cum.PastAid$		-0.041***		
		(0.005)		
Aid $\times PastAid(Lag)$			-0.024+	
			(0.014)	
Aid $\times MathHS(UL)$				-0.000
				(0.001)
Risk Set FE	X	X	X	X
Num.Obs.	35953	35953	24615	8603
Waivers				
Aid Receipt	0.075+	0.147**	0.144**	
	(0.040)	(0.045)	(0.044)	
Aid $\times CurrentCGPA$	-0.144***			
	(0.041)			
Aid $\times Cum.PastAid$		-0.036		
		(0.034)		
Aid $\times PastAid(Lag)$			-0.054	
			(0.065)	
Risk Set FE	X	X	X	
Num.Obs.	1263	1263	1069	

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

Note:
Results from two-stage least squares regressions estimating the impact of current aid receipt on the ultimate probability of graduation. The endogenous interactions test for dynamic complementarities across proxies of skill and resources for both stipends and waivers. All models include risk set fixed effects and control for the running variable. Robust standard errors clustered at the student level.

marginal effects (δ^M) used in the decomposition understate the true indirect benefit for the specific students who were crowded into receiving future aid. Thus, the decomposition subtracts a calculated crowd-in sum that is too small, leaving the estimated marginal effect of early aid on GPA as an upper bound. Conversely, for graduation, the estimated marginal effect represents a conservative lower bound. Because aid exhibits negative dynamic complementarity on the extensive margin, the average future effects overstate the true indirect benefit for already-treated students. By subtracting this overstated indirect effect, the resulting isolated marginal effect on graduation is biased downward and represents a lower bound.

5 Discussion and Conclusion

In this paper, I estimate the effect of financial aid that is competitively reassigned each semester based on student merit. Using a unique institutional setting in Latvia where tuition waivers and stipends are the only form of aid available to the vast majority of students, I provide causal evidence on the dynamic effects of these programs on student success.

I find that both tuition waivers and stipends have a significant positive impact on student outcomes, increasing their grades, persistence, and graduation rates. The total effects are large: receiving a tuition waiver increases a student's probability of graduation by 14 percentage points and their persistence into the next semester by 13 percentage points.

These estimated impacts are at the upper end of the range reported in prior financial aid evaluations, which is likely driven by the tournament-style incentives and the lack of alternative aid sources in this setting. The robustness of these findings is enhanced by the fixed curriculum, which limits students' ability to game the system through course selection and provides a cleaner measure of aid's impact on academic effort.

The central contribution of this paper is the identification of a powerful and persistent crowding-in effect, where receiving aid in one semester significantly increases the probability of receiving it in subsequent semesters. To understand the importance of this mechanism, I decompose the total effect of aid into its direct marginal impact and its indirect crowding-in impact. This analysis reveals that the crowding-in of future aid is a substantial driver of the large long-term benefits, particularly for aid awarded to students earlier in their studies.

While the baseline recursive decomposition model relies on an assumption of additive separability for tractability, I explicitly test the boundaries of this assumption by exploring dynamic complementarities in skill formation. By identifying that aid acts as a dynamic complement for short-term effort but as a compensatory substitute for long-term degree attainment, I am able to formally sign the bias of the dynamic estimator. I find that the marginal effects of early aid calculated in the decomposition represent an upper bound for academic performance, but a lower bound for graduation.

Diving deeper into the mechanisms of skill formation, this paper provides a structural test of the interaction between existing skills and financial aid investment. For short-term academic performance, stipends can act as a dynamic complement, multiplying the effort of students with higher baseline GPAs. However, for ultimate degree attainment, financial aid is deeply compensatory. The impact of both waivers and stipends on graduation is significantly magnified for students with lower existing levels of human capital and fewer prior resources. This presents a nuanced consideration for policymakers: while tournament structures effectively incentivize the top of the distribution to maximize effort, a large part of the long-term value of merit aid lies in retaining and graduating students at the bottom of the distribution who would otherwise drop out.

Finally, the findings from Latvia's unique setting offer several lessons for policy design in more complex aid environments. The power of the crowding-in effect demonstrates that policymakers should evaluate aid not as a series of one-off grants, but as a system that can create positive feedback loops over a student's entire academic career. The results also highlight a key tension in financial aid design: while tournaments effectively incentivize effort, there is a trade-off between the intensive and extensive margin of providing aid wherein aid can be provided broadly to support individuals who would otherwise not finish their education, or to elicit additional performance from students at the top.

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Appendices

A Density Tests for Sparse Data

The main assumption behind an RD design is that student potential outcomes are continuous across the cutoff, i.e. that the only student characteristics that suddenly change across the cutoff are their probability of treatment receipt. To support this assumption, there are multiple tests, with the two most prominent being a balance test of student characteristics (reported in Table 2), and a density test of whether there is differential heaping around the cutoff (Cattaneo et al., 2020; McCrary, 2008).

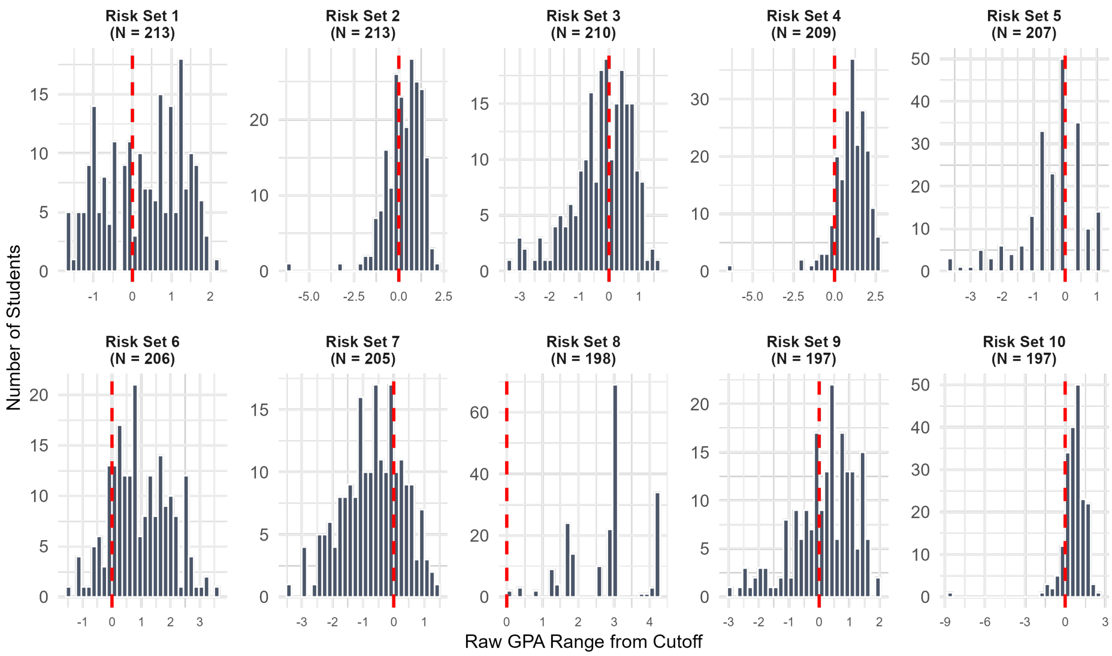
The core concern that these tests address is whether students are able to select into treatment or not. If students are able to select into treatment, then the RD estimator will be biased. The balance test looks at observable characteristics and sees whether those change discontinuously, and the density test looks at the heaping around the cutoff to see if people are differentially selecting into treatment, which would show up as a large number of individuals being just below or above the cutoff.

The way my data is constructed is that students take courses in a semester that can only take on full values ranging from 1 to 10, with the semester grade being the average of these values. Because of the way the data is generated, regular density tests would yield incorrect inference, because the discontinuous distributions could just as well be attributed to the data-generating process as to student selection into treatment.

The tournament-style provision of financial aid means that for students to be able to select into treatment, they would need to push another student out, which would inherently balance the densities across the cutoff. However, the null hypothesis of no discontinuity is rejected by the density tests due to the data-generating process.

I plot the 10 largest risk sets for stipends (Figure 12) and waivers (Figure 13). Thus, when looking at each risk set individually and at the raw scores, I do not find evidence of

Figure 12: Density of Raw GPA Scores for 10 Largest Stipend Risk Sets



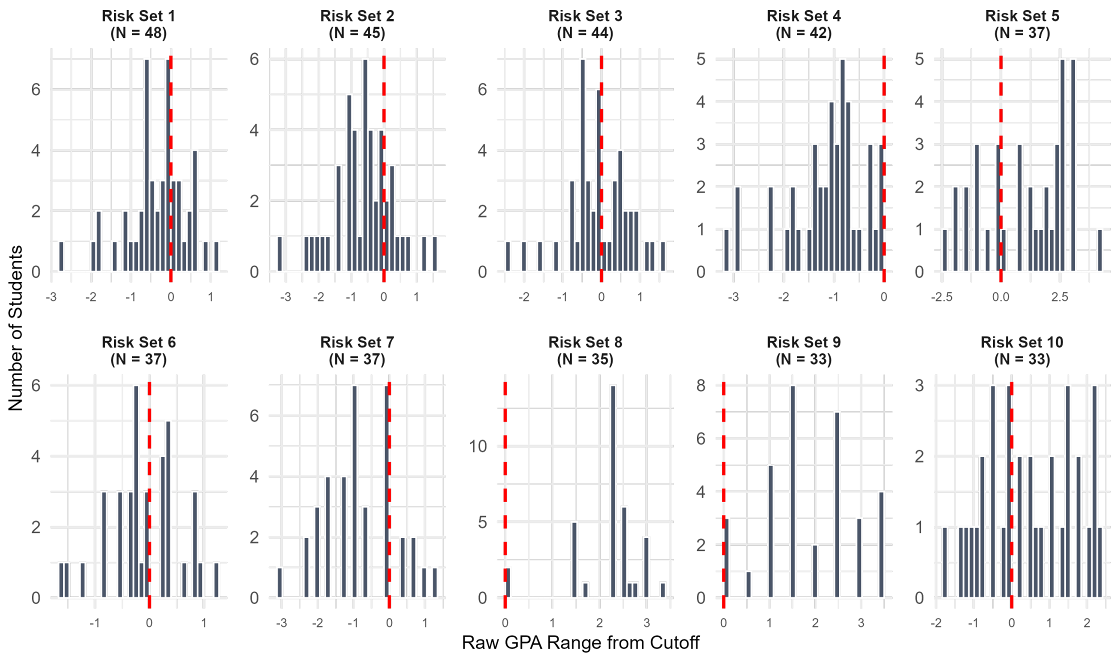
Note: These plots represent the density of the raw GPA of individuals in the 10 largest risk sets. The GPA has been recentered so that 0 is the cutoff at which the individual with the lowest GPA received aid.

individuals being able to precisely manipulate their GPA and self-select into aid reception.

To empirically estimate the degree to which there could be selective discontinuities across the cutoff, I use two different tests - a test for the discontinuity in the ratios of the conditional densities to the unconditional density (Zimmerman, 2014), and a permutation test. The permutation test is reported in the main section of the paper.

The conditional density ratio test looks at the conditional distribution of student densities across the cutoffs to see if they are continuous across the cutoff. The test looks at not only the continuous distribution of standardized grades across the cutoff, but of student conditional densities based on characteristics that impact their academic outcomes. I report the results of this test in Figure 14 for three different groups - male students, students from minority-language-of-instruction schools, and students from Riga. I find that each of the density ratios is continuous around the cutoff value.

Figure 13: Density of Raw GPA Scores for 10 Largest Waiver Risk Sets



Note: These plots represent the density of the raw GPA of individuals in the 10 largest risk sets. The GPA has been recentered so that 0 is the cutoff at which the individual with the lowest GPA received aid.

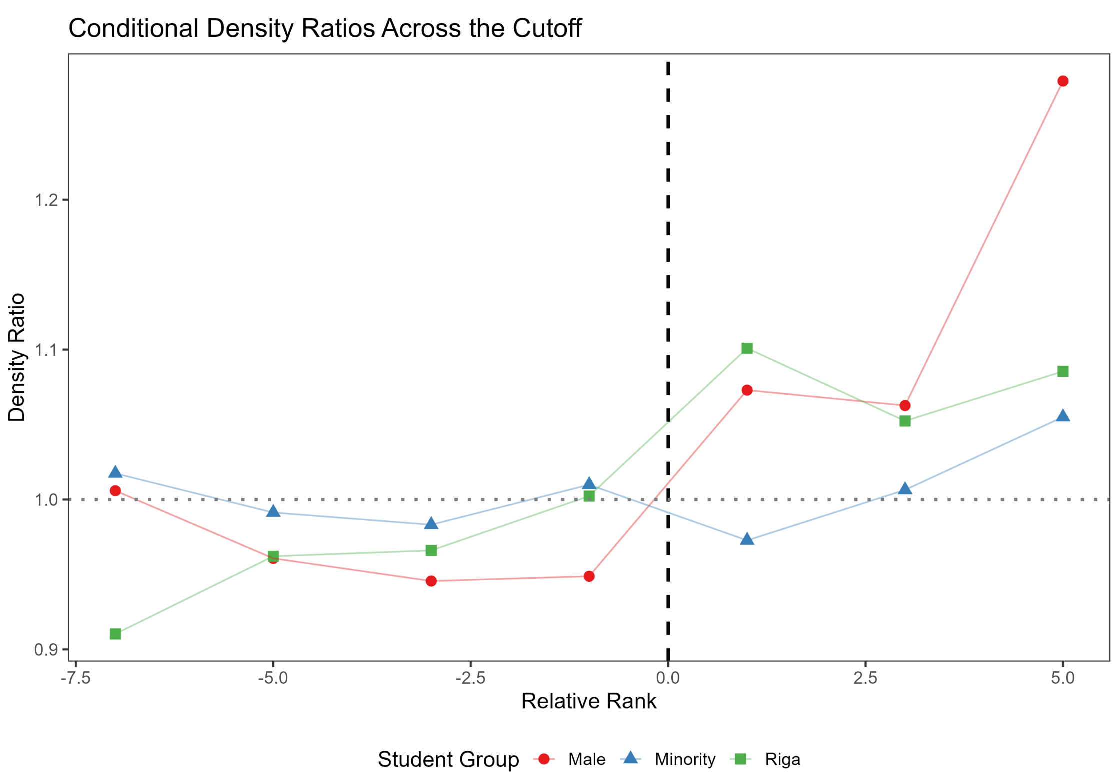


Figure 14: Conditional Density Ratio Test

Table 11: Estimation of Stipend Eligibility Effects with Different Bandwidths for RSU

	Bandwidth				
	(1)	(2)	(3)	(4)	(5)
GPA	0.132***	0.179***	0.179***	0.229***	0.326***
	(0.039)	(0.028)	(0.028)	(0.026)	(0.023)
Persistence	0.002	0.002	0.002	0.000	0.000
	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)
On Track	−0.001	0.003	0.003	0.000	0.001
	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)
Graduation	0.004	−0.004	−0.004	−0.005	0.010
	(0.014)	(0.010)	(0.010)	(0.009)	(0.008)
Dropout	−0.002	0.011	0.011	0.008	0.000
	(0.011)	(0.008)	(0.008)	(0.007)	(0.006)
Graduation on Time	0.046*	0.025+	0.025+	0.007	0.021+
	(0.018)	(0.013)	(0.013)	(0.013)	(0.012)
Risk Set FE	9967.000	15 352.000	15 352.000	18 412.000	21 868.000

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

Note: The table reports reduced-form estimates of stipend eligibility estimated using varying bandwidths of the running variable (relative rank). Column headers indicate the bandwidth size in rank positions. Persistence is defined as an indicator for whether the student is enrolled in the university in the following semester. All models include risk set fixed effects. Robust standard errors clustered at the student level in parentheses.

B Robustness Tests

I also conduct robustness tests by varying the bandwidth (tables 12 and 11). I find that my results are robust to different bandwidth specifications.

I also conduct robustness tests by varying the point at which the cutoff occurs and similarly find that centering the cutoff at 0 provides the strongest predicted probability of treatment.

I also conduct these tests for UL and find that the results are also robust.

Finally, I also use the estimation approach by Armstrong and Kolesár (2020) to conduct tests using their suggested RD estimation approach. I let the bandwidth vary for each outcome variable and aid type and estimate the reduced form estimates in 16 and

Table 12: Estimation of Waiver Eligibility Effects with Different Bandwidths

	Bandwidth				
	(1)	(2)	(3)	(4)	(5)
GPA	0.326+	0.357+	0.420***	0.378***	0.418***
	(0.193)	(0.208)	(0.091)	(0.101)	(0.075)
Persistence	0.107**	0.095+	0.107***	0.079**	0.091***
	(0.038)	(0.049)	(0.022)	(0.025)	(0.017)
On Track	0.070+	0.072	0.094***	0.065**	0.081***
	(0.039)	(0.046)	(0.022)	(0.024)	(0.017)
Graduation	0.221*	0.267**	0.132**	0.148***	0.087*
	(0.085)	(0.088)	(0.042)	(0.043)	(0.036)
Dropout	−0.188**	−0.167*	−0.130***	−0.131***	−0.090***
	(0.060)	(0.072)	(0.033)	(0.035)	(0.027)
Graduation on Time	0.148	0.235*	0.122*	0.113*	0.102*
	(0.107)	(0.110)	(0.050)	(0.057)	(0.041)
Risk Set FE	458.000	771.000	1592.000	1418.000	1952.000

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

Note: The table reports reduced-form estimates of waiver eligibility estimated using varying bandwidths of the running variable (relative rank). Column headers indicate the bandwidth size in rank positions. Persistence is defined as an indicator for whether the student is enrolled in the university in the following semester. All models include risk set fixed effects. Robust standard errors clustered at the student level in parentheses.

Table 13: Estimation of First Stage with Various Cutoffs for RSU

	Cutoff Value				
	-2	-1	0	1	2
Stipends					
Stipend	-0.076***	0.028+	0.557***	0.449***	0.304***
	(0.016)	(0.016)	(0.010)	(0.010)	(0.010)
Num.Obs.	15401	15978	16360	16705	17075
Waivers					
Waiver	-0.325***	-0.140***	0.769***	0.508***	0.243***
	(0.041)	(0.039)	(0.023)	(0.030)	(0.028)
Num.Obs.	1776	1826	1864	1854	1778
Risk Set FE	X	X	X	X	X

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

Note: The table reports first-stage estimates using placebo cutoffs (artificially shifting the cutoff rank). The dependent variable is aid receipt. Column headers indicate the shift in the cutoff rank. All models include risk set fixed effects. Robust standard errors clustered at the student level in parentheses.

Table 14: Estimation of Stipend Eligibility Effects with Different Bandwidths for UL

	Bandwidth				
	(1)	(2)	(3)	(4)	(5)
GPA	0.187***	0.204***	0.285***	0.364***	0.410***
	(0.027)	(0.025)	(0.021)	(0.019)	(0.018)
Persistence	0.064***	0.066***	0.061***	0.065***	0.073***
	(0.009)	(0.008)	(0.007)	(0.006)	(0.006)
On Track	0.071***	0.076***	0.093***	0.103***	0.119***
	(0.012)	(0.011)	(0.009)	(0.009)	(0.008)
Graduation	0.086***	0.088***	0.087***	0.093***	0.103***
	(0.011)	(0.010)	(0.009)	(0.008)	(0.007)
Graduation on Time	0.064***	0.070***	0.092***	0.103***	0.119***
	(0.012)	(0.011)	(0.009)	(0.009)	(0.008)
Risk Set FE	21 907.000	24 220.000	30 922.000	35 760.000	38 629.000

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

Note: The table reports the estimates from regressions from a reduced-form regression for various bandwidths. Robust standard errors clustered at the student level in parentheses.

Table 15: Estimation of First Stage with Various Cutoffs for UL

	Cutoff Value				
	-2	-1	0	1	2
Stipend	-0.250***	0.157***	0.949***	0.541***	0.182***
	(0.007)	(0.008)	(0.004)	(0.007)	(0.006)
Risk Set FE	X	X	X	X	X
Num.Obs.	21 201	22 828	24 231	25 326	26 125

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

Note: The table reports the estimates from regressions of student of receiving aid on whether they are above the cutoff or not for various cutoff values with risk set fixed effects. Robust standard errors clustered at the student level in parentheses.

2SLS estimates in Table 17. I generally find broadly similar outcomes as with my main specification.

Table 16: Effect of Aid on Student Outcomes with Armstrong and Kolesar (2020) CIs

	GPA	Persistence	On Track	Graduation	Dropout	On Time
Stipends						
RD Estimate	0.151***	0.048***	0.056***	0.069***	0.012	0.063***
	(0.023)	(0.006)	(0.008)	(0.008)	(0.007)	(0.009)
Waivers						
RD Estimate	0.297*	0.083**	0.063*	0.132**	-0.174*	0.104
	(0.128)	(0.027)	(0.026)	(0.044)	(0.059)	(0.054)

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

Note:
The table reports bias-corrected robust RD estimates (Armstron and Kolesár, 2020) for student outcomes. Bandwidths are MSE-optimal. Persistence is defined as an indicator for whether the student is enrolled in the university in the following semester. On Track is defined as an indicator for whether the student progresses to the next academic semester in the following term. All models include risk set fixed effects.

Table 17: 2SLS Estimates of the Effect of Aid with Armstrong and Kolesar (2020) CIs

	(1)
GPA	
RD Estimate	0.177***
	(0.027)
Persistence	
RD Estimate	0.057***
	(0.007)
On Track	
RD Estimate	0.066***
	(0.009)
Graduation	
RD Estimate	0.080***
	(0.009)
Dropout	
RD Estimate	0.021
	(0.013)
On Time	
RD Estimate	0.073***
	(0.010)

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

Note:
The table reports bias-corrected robust RD estimates (Armstron and Kolesár, 2020) for student outcomes. Bandwidths are MSE-optimal. Persistence is defined as an indicator for whether the student is enrolled in the university in the following semester. On Track is defined as an indicator for whether the student progresses to the next academic semester in the following term. All models include risk set fixed effects.

C The One-Step Dynamic RD Method

As a complementary approach, I also adapt the one-step dynamic RD estimator (Cellini et al., 2010) to estimate the dynamic impact profile of past eligibility events on current outcomes. The difference between the one-step estimate and the recursive estimate would be that the recursive estimate described in the previous section is that the recursive estimate estimates the marginal contribution of aid in different semesters on a student's outcome.

The one-step estimator, on the other hand, estimates the impact of aid reception after time t, without being able to decompose the impact into direct and indirect effects. Another way to think about it would be to think of the one-step estimator as estimating the decay pattern of financial aid, while holding aid history constant.

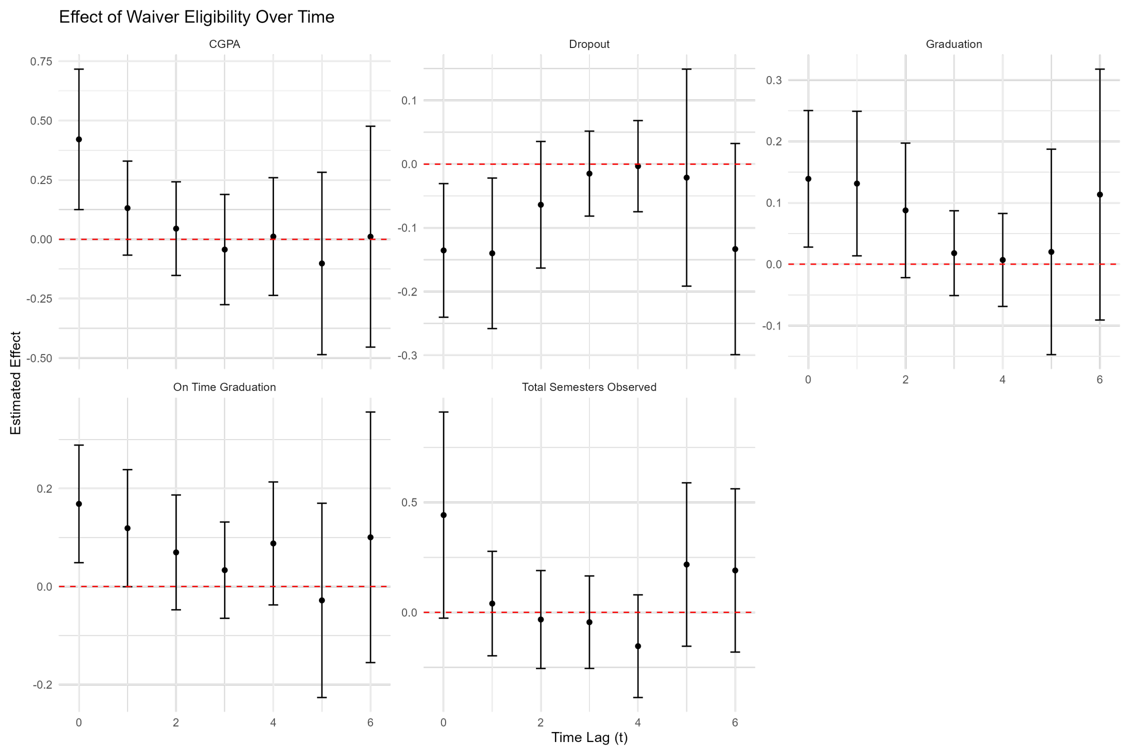
The benefits of the one-step dynamic RD approach is that it uses the full history of observations for each individual, thus increasing statistical power. It also estimates the impact of financial aid over time. Using this method, I estimate the following model using panel data:

$$Y_{ijt} = \beta_0 Above_{ijt} + f_0(r_{ijt}) + \sum_{\tau=1}^{\bar{\tau}} \left[\beta_\tau Above_{ijt-\tau} + f_\tau(r_{ijt-\tau}) \right] + \lambda_j + \omega_t + \epsilon_{ijt} \tag{10}$$

where $Above_{ijt-\tau}$ indicates eligibility status τ semesters prior, $f_\tau(r_{ijt-\tau})$ is a flexible function of the rank from τ semesters prior, λ_j represents risk-set fixed effects, and ω_t denotes semester fixed effects. The coefficients β_τ estimate the average effect for individuals above the cutoff τ periods in the past on the current outcome Y_{ijt}, conditional on the history of eligibility and rank included in the model. Plotting β_τ against the lag τ directly illustrates the impact over time, or decay pattern, of initial eligibility. While estimating a different parameter than the marginal effect $\delta^M_{t,t+k}$ from the recursive method, this approach provides valuable insights into effect duration and will offer greater statistical precision for estimating the persistence pattern itself, as it will leverage the full dataset.

Additionally, for the one-step estimator I use the same subset of individuals as I use for

Figure 15: One-shot estimator results for waivers



Note: These figures show the results of the one-shot estimator for waivers for undergraduate students with a program length of 8 semesters. The figures report the estimates on waiver receipt in past on current grades, with the x axis reporting the lag.

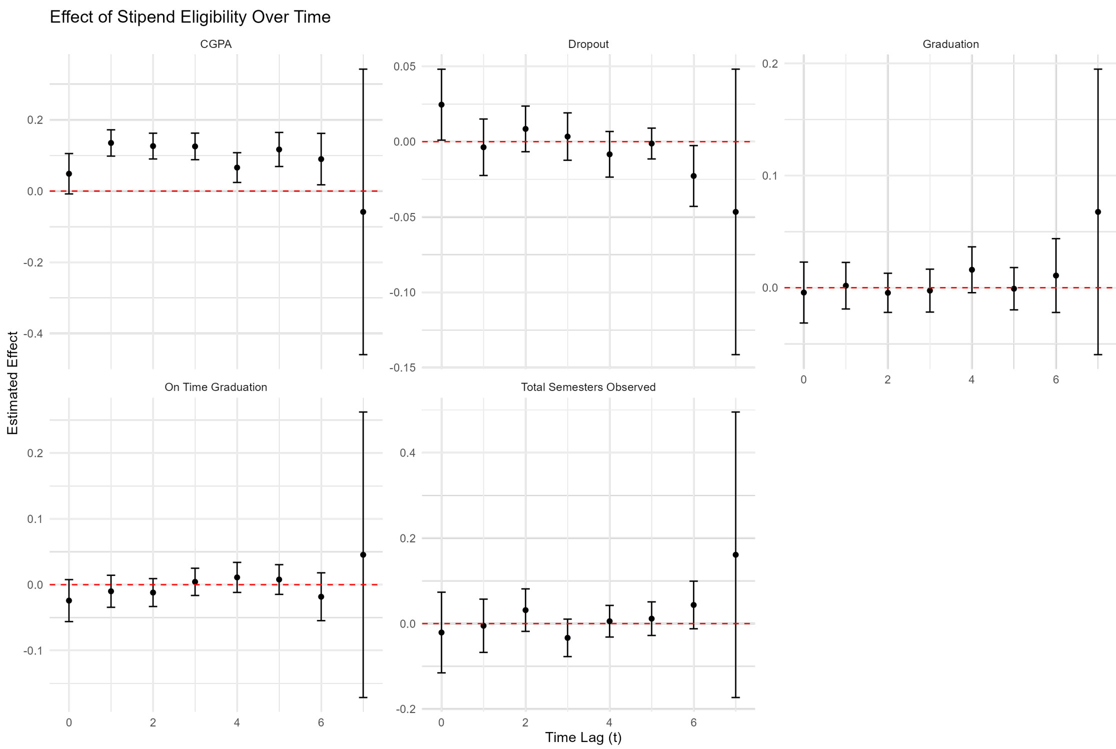
the dynamic decomposition - people in undergraduate programs with a program length of 8 semesters.

I find that even when controlling for aid history, financial aid in past semesters has strong effects on outcomes in the current semesters, with waivers having impact two semesters ahead (Figure 15) and stipends having extensive and pronounced impact on GPA throughout the observed history (Figure 16)

Additionally, I explore the heterogeneity of financial aid impact decay by conditions of the competition. As waivers received in the fall are guaranteed for two semesters, I study how financial aid receipt in the fall compared to the spring impacts the effects over time in figures 16 and 18. I generally do not find differential impacts of having more stable waivers for students.

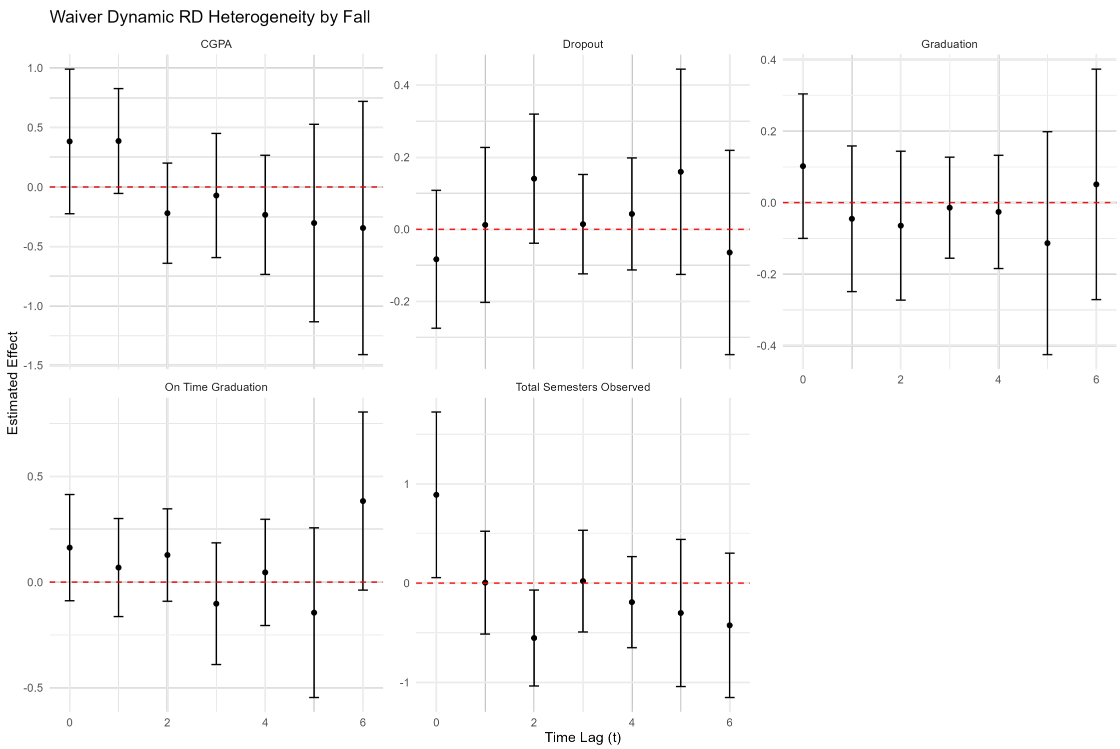
Finally, given that some students have guaranteed waivers throughout their studies

Figure 16: One-shot estimator results for stipends



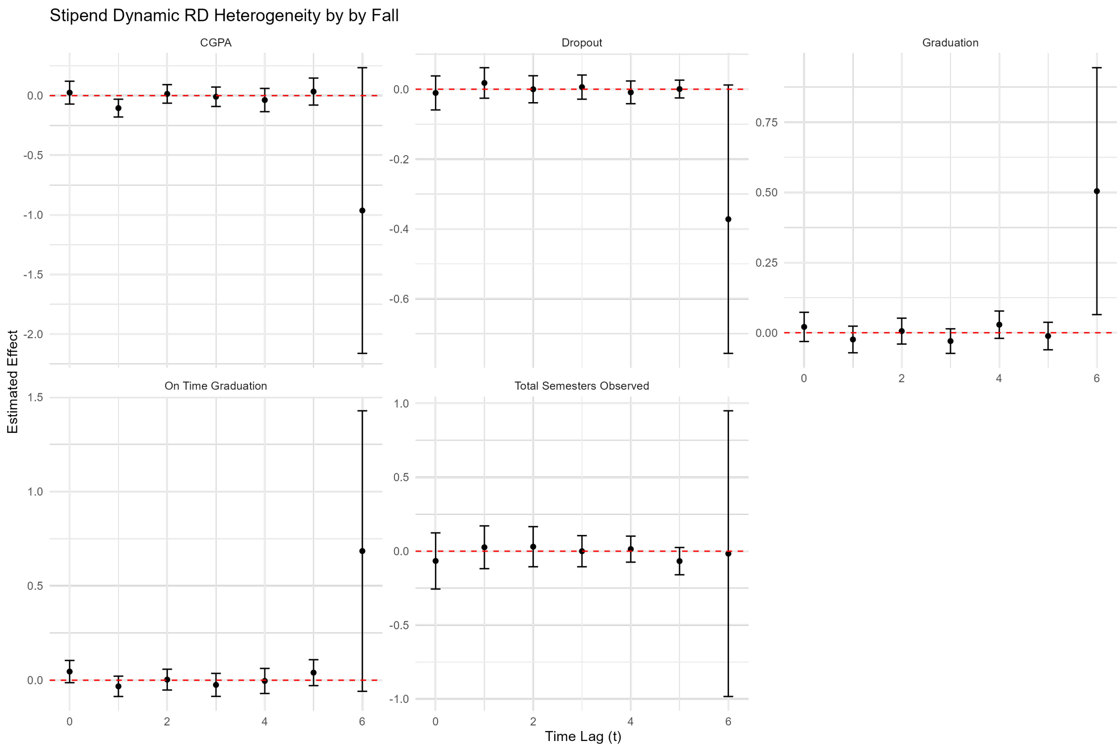
Note: These figures show the results of the one-shot estimator for stipends for undergraduate students with a program length of 8 semesters. The figures report the estimates on stipend receipt in past on current grades, with the x axis reporting the lag.

Figure 17: One-shot estimator heterogeneity for waivers in the fall



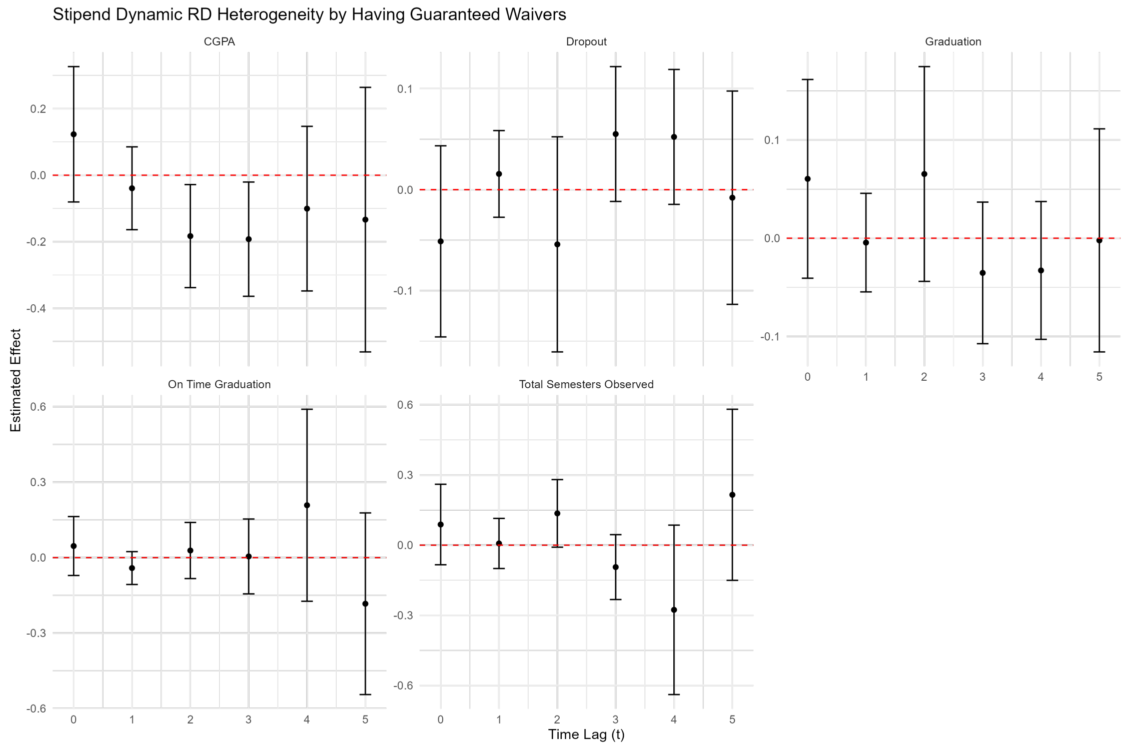
Note: These figures show the results of the interaction term between past aid and receiving it in the fall for the one-shot estimator for waivers for undergraduate students with a program length of 8 semesters. The figures report the estimates on waiver receipt in past on current grades, with the x axis reporting the lag.

Figure 18: One-shot estimator heterogeneity for stipends in the fall



Note: These figures show the results of the interaction term between past aid and receiving it in the fall for one-shot estimator for stipends for undergraduate students with a program length of 8 semesters. The figures report the estimates on stipend receipt in past on current grades, with the x axis reporting the lag.

Figure 19: One-shot estimator heterogeneity for stipends for those guaranteed aid



Note: These figures show the results of the interaction term between past aid and having a guaranteed waiver for one-shot estimator for stipends for undergraduate students with a program length of 8 semesters. The figures report the estimates on stipend receipt in past on current grades, with the x axis reporting the lag.

if they received a waiver upon enrolment, I conduct a heterogeneity analysis for stipend impacts by interacting stipend aid receipt with whether the student had a guaranteed waiver or not (Figure 19).

I find that individuals who received stipends while in guaranteed waiver seats see smaller impacts on their GPA over time, potentially driven by the security effect of having a guaranteed tuition waiver. This heterogeneity only applies to CGPA, with no significant difference for other variables such as dropout, graduation or persistence, implying that the main margin that stipends motivate students in RSU is through increased academic performance, but not affecting their academic progression.

D Institution-Specific Stipend Impacts (RSU and UL)

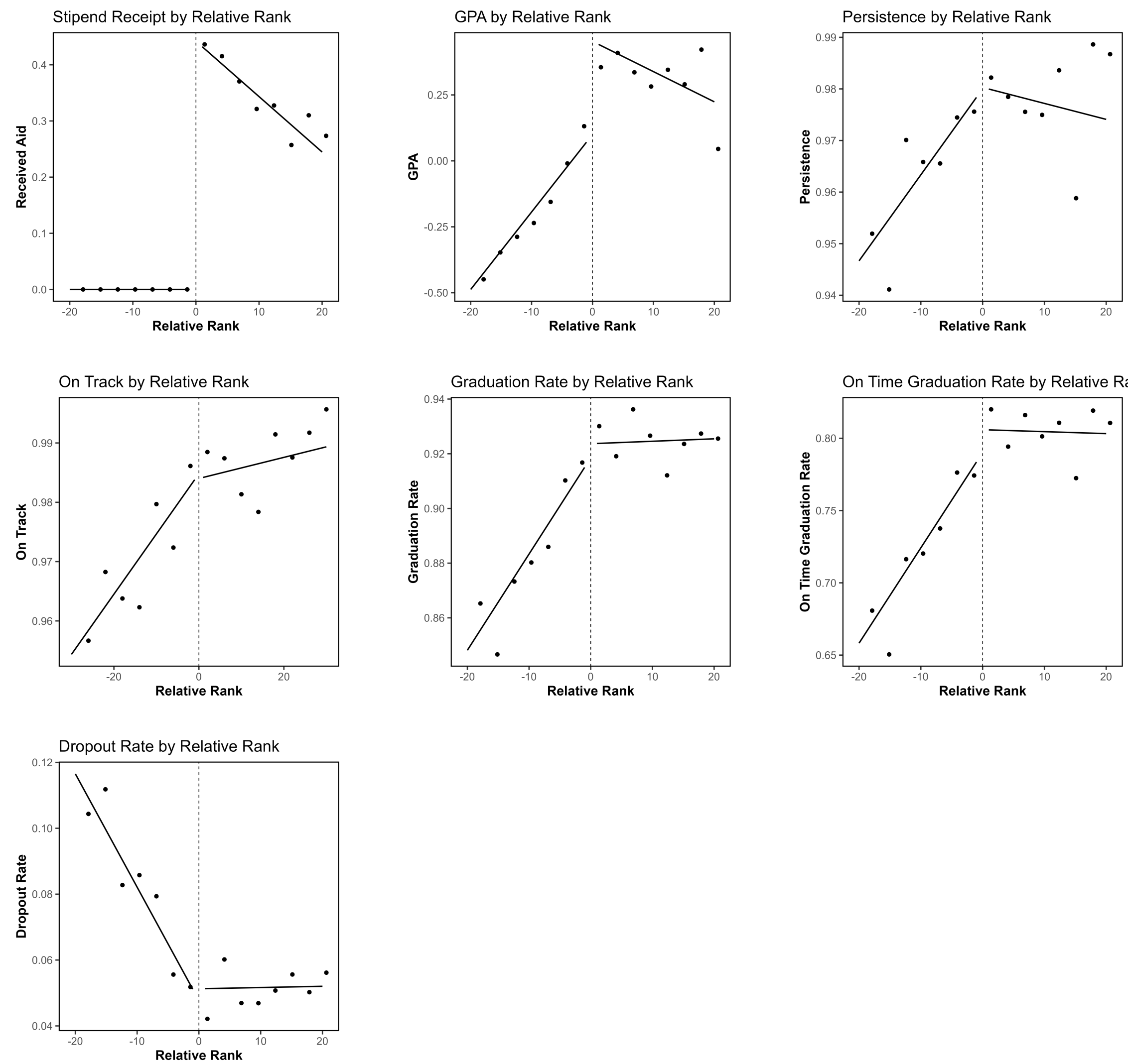
While the main text pools data across Riga Stradiņš University (RSU) and the University of Latvia (UL) to maximize power, the institutional assignment mechanisms differ slightly. RSU incorporates scientific performance into its stipend assignments and guarantees waivers for enrolled students, while UL uses a strict GPA cutoff. This section disentangles the total impacts of stipend receipt by institution.

D.1 Results for Riga Stradiņš University (RSU)

This subsection details the stipend impacts specifically for the Riga Stradiņš University (RSU) cohort. At RSU, a significant portion of the student body already holds a guaranteed tuition waiver upon enrollment. Consequently, the tournament for stipends operates under slightly different stakes than a purely open competition. As shown in Table 18, the overall impact of winning a stipend at RSU is concentrated primarily on the intensive margin, boosting next-semester GPA by 0.306, with a weaker average effect on extensive margins like persistence or graduation.

However, exploring heterogeneity reveals nuanced dynamics for this specific institution. Table 6 demonstrates that for students in their first year, the impact of stipends on academic effort is positive (increasing GPA by 0.114σ), though it yields only marginal increases in persistence (1.5pp). The safety net of guaranteed waivers has profound behavioral effects at RSU. Table 21 shows that for students who already possess a guaranteed waiver, winning a stipend induces a strong complacency effect, decreasing next-semester GPA by 0.318 standard deviations with no significant effect on persistence. Interestingly, in more difficult risk sets (below-median GPA), winning a stipend induces students to significantly improve their grades (by 0.141 standard deviations) but negatively impacts their persistence (-1.2 percentage points).

Figure 20: Student Outcomes Below and Above the Stipend Reception Threshold for RSU



Note: These figures show the change in student outcomes based on distance from the rank cutoff for reception of stipends. The plotted points are binned averages of the dependent variable, residualized by risk-set fixed effects. The lines are linear fits to the residualized data separately for each side of the cutoff.

D.2 Results for the University of Latvia (UL)

This subsection details the stipend impacts specifically for the University of Latvia (UL) cohort. Unlike RSU, UL utilizes a strict, GPA-only cutoff for stipend eligibility and does

Table 18: Effect of Stipends on Student Outcomes in the Next Semester

	OLS	Risk Set FE	2SLS	Per €1k
GPA in Next Semester	0.175***	0.175***	0.306***	0.569***
	(0.028)	(0.028)	(0.048)	(0.090)
Persisted in Next Semester	0.010*	0.002	0.004	0.007
	(0.004)	(0.004)	(0.008)	(0.014)
On Track in Next Semester	0.013***	0.003	0.005	0.009
	(0.004)	(0.004)	(0.007)	(0.013)
Graduation	0.055***	−0.004	−0.006	−0.012
	(0.012)	(0.010)	(0.018)	(0.034)
Dropped Out	−0.024**	0.011	0.020	0.037
	(0.008)	(0.008)	(0.014)	(0.025)
Graduation on Time	0.065***	0.024+	0.042+	0.081+
	(0.015)	(0.013)	(0.024)	(0.046)
Risk Set FE		X	X	X
Num.Obs.	16 360	16 360	16 360	16 360

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

Note: The table reports intent-to-treat (reduced form) and instrumental variable (2SLS) estimates of the effect of stipend eligibility on student outcomes. 'Reduced Form' estimates are from a local linear regression of the outcome on the eligibility indicator. '2SLS' estimates instrument actual stipend receipt with eligibility. Persistence is defined as an indicator for whether the student is enrolled in the university in the following semester. On Track is defined as an indicator for whether the student progresses to the next academic semester in the following term (e.g. from semester 1 to semester 2). All models include risk set fixed effects and cluster standard errors at the student level. The minimum, maximum, and average first-stage F-statistics across the 2SLS models are 2627.4, 3222.6, and 2992.2 respectively.

Table 19: Heterogeneity by Student Demographics in the Effects of Stipends on Student Outcomes for RSU

	Heterogeneity Variable				
Outcome	Fees	Male	Age	Capital	Minority
GPA	0.000	0.068	0.012***	−0.057	−0.046
	(0.000)	(0.052)	(0.003)	(0.035)	(0.050)
Persistence	0.000	−0.001	0.000	0.006	−0.008
	(0.000)	(0.007)	(0.001)	(0.005)	(0.006)
On Track	0.000	−0.004	0.000	0.007	−0.007
	(0.000)	(0.007)	(0.001)	(0.005)	(0.006)
Dropout	0.000*	0.011	−0.003***	0.009	−0.008
	(0.000)	(0.015)	(0.001)	(0.009)	(0.014)
Graduation	0.000	−0.025	0.006***	−0.011	−0.001
	(0.000)	(0.018)	(0.001)	(0.012)	(0.017)
Ontime Grad.	0.000	0.004	0.005**	−0.014	0.006
	(0.000)	(0.030)	(0.002)	(0.018)	(0.026)
Risk Set FE	X	X	X	X	X
Num.Obs.	15 534	16 360	15 915	15 919	15 919

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

Note: The table reports heterogeneity analysis of stipend eligibility effects. Each column reports the coefficient on the interaction term between the eligibility indicator and the column variable (e.g., 'Male'). Persistence is defined as an indicator for whether the student is enrolled in the university in the following semester. All regressions include risk set fixed effects, controls for the running variable, and the main effects of the heterogeneity variable. Robust standard errors clustered at the student level in parentheses.

Table 20: Heterogeneity by Cutoff Characteristics for RSU

	Heterogeneity Variable				
Outcome	Cutoff Percentile	First Year	First Half	Last Year	Last Semester
GPA	0.149+	0.114**	0.090**	0.078*	−0.041
	(0.087)	(0.035)	(0.033)	(0.032)	(0.048)
Persistence	−0.057***	0.015**	0.016**	−0.018***	0.005
	(0.014)	(0.006)	(0.005)	(0.005)	(0.007)
On Track	−0.055***	0.016**	0.016***	−0.017***	0.004
	(0.013)	(0.005)	(0.005)	(0.004)	(0.007)
Dropout	0.103***	−0.019	−0.014	0.014+	−0.019+
	(0.023)	(0.013)	(0.009)	(0.009)	(0.010)
Graduation	−0.086**	0.026	0.022+	−0.018	0.012
	(0.029)	(0.017)	(0.012)	(0.011)	(0.012)
Ontime Grad.	−0.112**	0.014	0.031*	−0.029+	−0.001
	(0.041)	(0.020)	(0.015)	(0.015)	(0.018)
Risk Set FE	X	X	X	X	X
Num.Obs.	16 360	16 360	16 327	16 327	16 327

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

Note: The table reports heterogeneity analysis by characteristics of the cutoff itself. Each column reports the coefficient on the interaction term between eligibility and the characteristic. 'Cutoff Percentile' is the percentile rank of the cutoff within the risk set. 'First Year' indicates if the student is in their first year of study. Persistence is defined as an indicator for whether the student is enrolled in the university in the following semester. Robust standard errors clustered at the student level in parentheses.

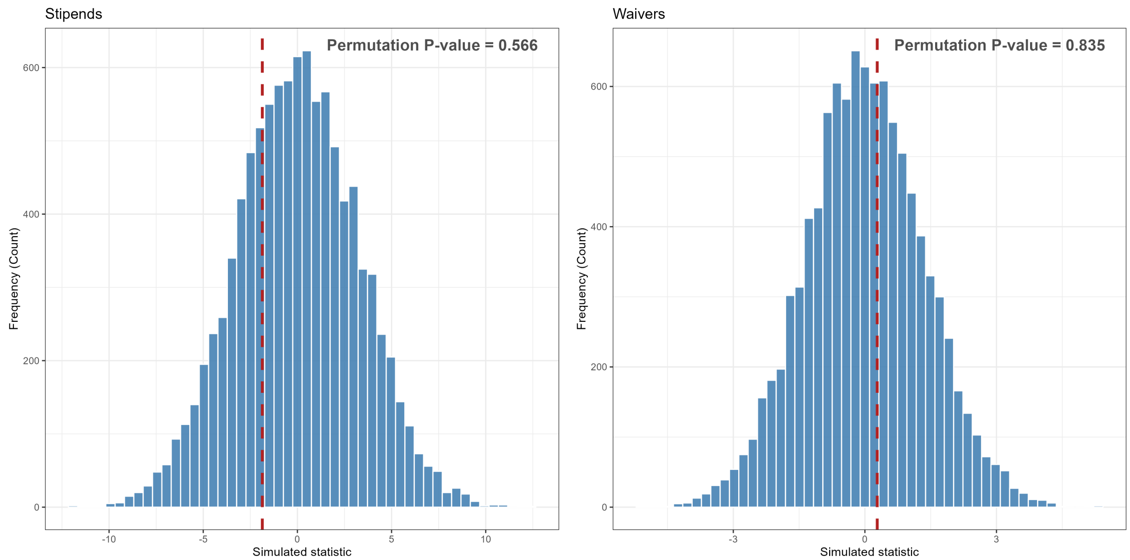
Table 21: Heterogeneity by Competitiveness in the Effects of Stipends on Student Outcomes for RSU

	Heterogeneity Variable			
Outcome	Fall	<Median GPA	<Median Progression	Guaranteed Aid
GPA	0.071*	0.141***	−0.131***	−0.318***
	(0.030)	(0.036)	(0.037)	(0.078)
Persistence	0.005	−0.012*	0.046***	−0.001
	(0.005)	(0.005)	(0.008)	(0.009)
On Track	0.002	−0.013**	0.047***	−0.001
	(0.005)	(0.005)	(0.008)	(0.008)
Dropout	−0.033***	−0.005	−0.024*	0.004
	(0.008)	(0.010)	(0.011)	(0.017)
Graduation	0.033***	−0.006	0.034*	−0.028
	(0.009)	(0.012)	(0.015)	(0.026)
Ontime Grad.	0.046***	−0.011	0.033+	−0.046
	(0.013)	(0.018)	(0.019)	(0.040)
Risk Set FE	X	X	X	X
Num.Obs.	16 360	16 360	16 360	16 360

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

Note: The table reports heterogeneity analysis by various measures of competitiveness. Each column reports the coefficient on the interaction term between eligibility and the column variable. 'Fall' indicates the Fall semester. '¡Median GPA' and '¡Median Progression' indicate higher difficulty risk sets based on below-median baseline averages. 'Guaranteed Aid' indicates students who started with a waiver. All regressions include risk set fixed effects, controls for the running variable, and the main effects of the heterogeneity variable. Robust standard errors clustered at the student level in parentheses.

Figure 21: Distribution of Density Test Values for RSU



Note: These figures show the distribution of density test values for the dataset wherein the cutoff values are randomly reassigned within risk sets. Line indicates density test value for observed data.

not offer the same widespread safety net of guaranteed waivers. This creates a sharper tournament environment where the stakes for academic performance are higher.

Consequently, the baseline 2SLS estimates for UL (Table 23) reveal impacts across both the intensive margin (GPA increases by 0.213 σ) and the extensive margins (persistence increases by 6.9pp, and graduation by 9.3pp). For these students, the liquidity provided by a stipend plays a critical role in ensuring they can remain enrolled and complete their degrees.

Heterogeneity analysis further underscores the retention value of stipends in high-stakes environments. Table 24 shows that in less competitive or struggling cohorts (below-median GPA), stipends have smaller impacts on student GPA and graduation, but below-median progression risk sets see larger impacts on persistence. Similarly to RSU, the timing of the award matters (Table 25): early stipends in the first half of a student's studies are vital for persistence, while late stipends primarily drive final GPA.

Table 22: Balance Test for UL

	No FE	Risk Set FE
Female	−0.020+	−0.014
	(0.011)	(0.010)
Age	0.145	0.288**
	(0.115)	(0.096)
Capital	0.011	0.016
	(0.013)	(0.013)
Minority	0.001	−0.001
	(0.009)	(0.008)
Math CE	2.049**	0.883
	(0.718)	(0.569)
Risk Set FE		X
Num.Obs.	23 574	23 574

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

Note: The table reports balance tests testing for discontinuities in baseline characteristics at the cutoff. Estimates are from a local linear regression with a uniform kernel within the optimal bandwidth. The running variable is the student's relative rank. 'Risk Set FE' indicates the inclusion of risk set fixed effects. Standard errors are clustered at the student level.

Figure 22: Distribution of Density Test Values for UL

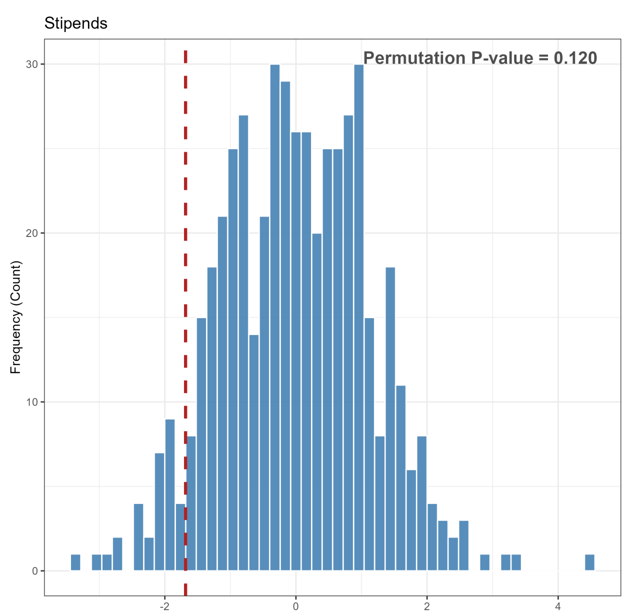
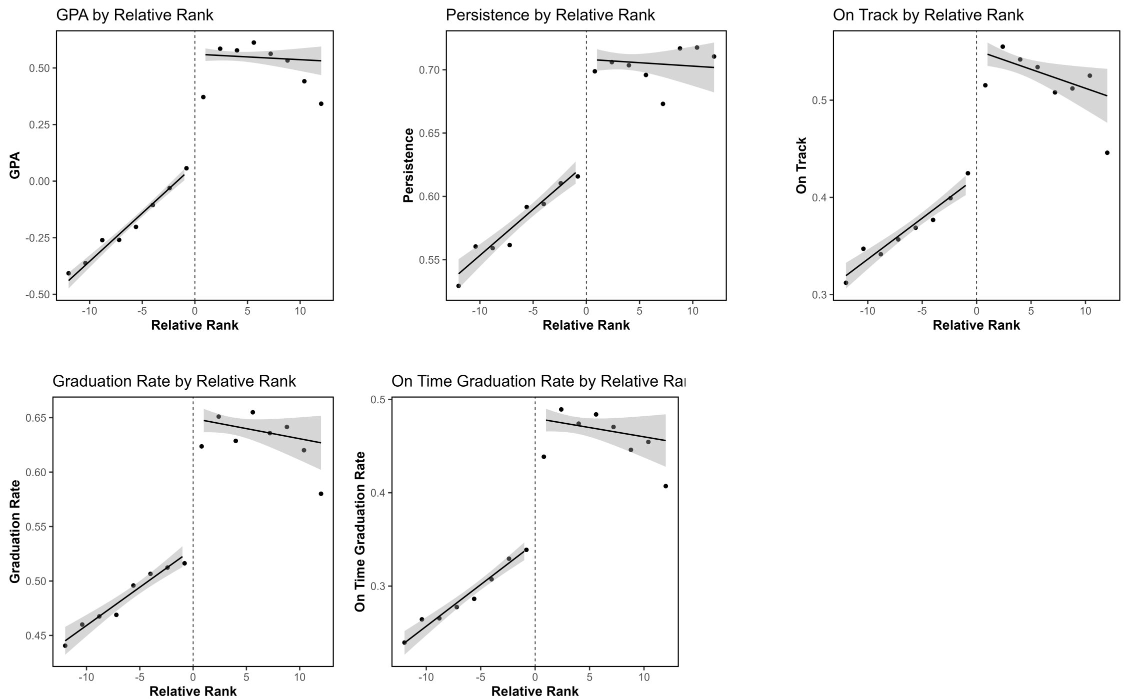


Figure 23: Student Outcomes Below and Above the Stipend Reception Threshold for UL



Note: These figures show the change in student outcomes based on distance from the rank cutoff for the reception of stipends. The plotted points are binned averages of the dependent variable, residualized by risk-set fixed effects. The lines are linear fits to the residualized data separately for each side of the cutoff.

Table 23: Effect of Stipends on Student Outcomes in the Next Semester in UL

	OLS	Risk Set FE	2SLS	Per €1k
GPA in Next Semester	0.253***	0.204***	0.213***	0.428***
	(0.026)	(0.025)	(0.026)	(0.053)
Persisted in Next Semester	0.066***	0.066***	0.069***	0.135***
	(0.011)	(0.008)	(0.009)	(0.017)
On Track in Next Semester	0.083***	0.076***	0.080***	0.182***
	(0.012)	(0.011)	(0.012)	(0.021)
Graduation	0.116***	0.088***	0.093***	0.156***
	(0.012)	(0.010)	(0.011)	(0.023)
Graduation on Time	0.091***	0.070***	0.074***	0.145***
	(0.012)	(0.011)	(0.012)	(0.023)
Risk Set FE		X	X	X
Num.Obs.	24 231	24 231	24 231	24 231

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

Note: The table reports estimates for various student outcomes. 'OLS' is the simple reduced-form estimate. 'Risk Set FE' includes fixed effects. '2SLS' instruments aid receipt with eligibility at the GPA cutoff. The minimum, maximum, and average first-stage F-statistics across the 2SLS models are 52894.9, 65129.5, and 61032.3 respectively, indicating a strong instrument.

Table 24: Heterogeneity by Competitiveness in the Effects of Stipends on Student Outcomes in UL

	<Median GPA	<Median Progression
GPA	−0.141**	0.053
	(0.050)	(0.051)
Persistence	0.019	0.032+
	(0.018)	(0.017)
On Track	−0.016	−0.005
	(0.023)	(0.022)
Graduation	−0.036+	0.007
	(0.021)	(0.020)
Ontime	−0.016	−0.012
	(0.022)	(0.021)
Aid Receipt	−0.017*	−0.002
	(0.007)	(0.007)
Risk Set FE	X	X
Num.Obs.	24 231	24 231

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

Note: The table reports heterogeneity analysis of aid eligibility effects by measures of competitiveness. Each column reports the coefficient on the interaction term between the eligibility indicator and the column variable. High difficulty is defined as a risk set being below the median raw GPA or rate of students progressing on track. All regressions include risk set fixed effects, controls for the running variable, and the main effects of the heterogeneity variable. Robust standard errors clustered at the student level in parentheses.

Table 25: Heterogeneity by Cutoff Characteristics for UL

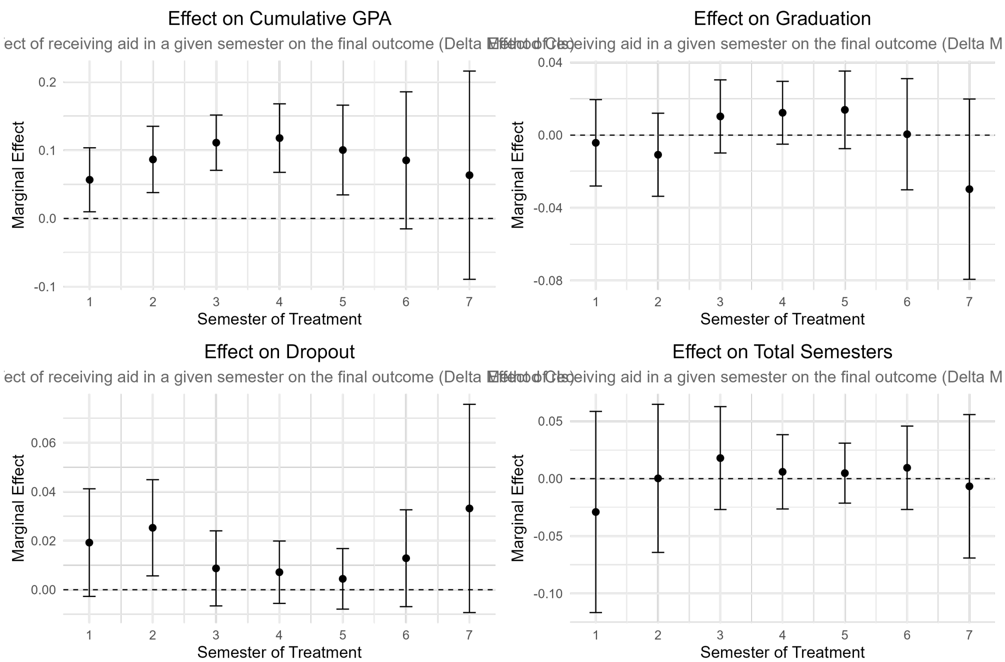
	Heterogeneity Variable			
Outcome	Cutoff Percentile	First Half	Last Year	Last Semester
GPA	−0.064	−0.187***	0.083	0.791
	(0.150)	(0.050)	(0.054)	(0.586)
Persistence	−0.016	0.045**	−0.042**	−0.071***
	(0.054)	(0.016)	(0.015)	(0.011)
On Track	−0.052	0.028	−0.017	−0.090**
	(0.062)	(0.022)	(0.023)	(0.031)
Graduation	−0.044	0.016	−0.013	−0.085***
	(0.059)	(0.020)	(0.019)	(0.017)
Ontime	−0.026	0.030	−0.019	−0.083**
	(0.057)	(0.021)	(0.022)	(0.030)
Aid Receipt	0.400***	0.000	0.010	0.002
	(0.035)	(0.007)	(0.007)	(0.010)
Risk Set FE	X	X	X	X
Num.Obs.	24 231	24 231	24 231	24 231

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

Note: The table reports the estimates from a series of regressions estimating the impact of being eligible financial aid on student grades, persistence, being on track in the next semester, graduation and graduation on time. Each estimate is from a separate regression. Persistence is defined as the student still being enrolled in a given semester. Robust standard errors clustered at the student level in parentheses.

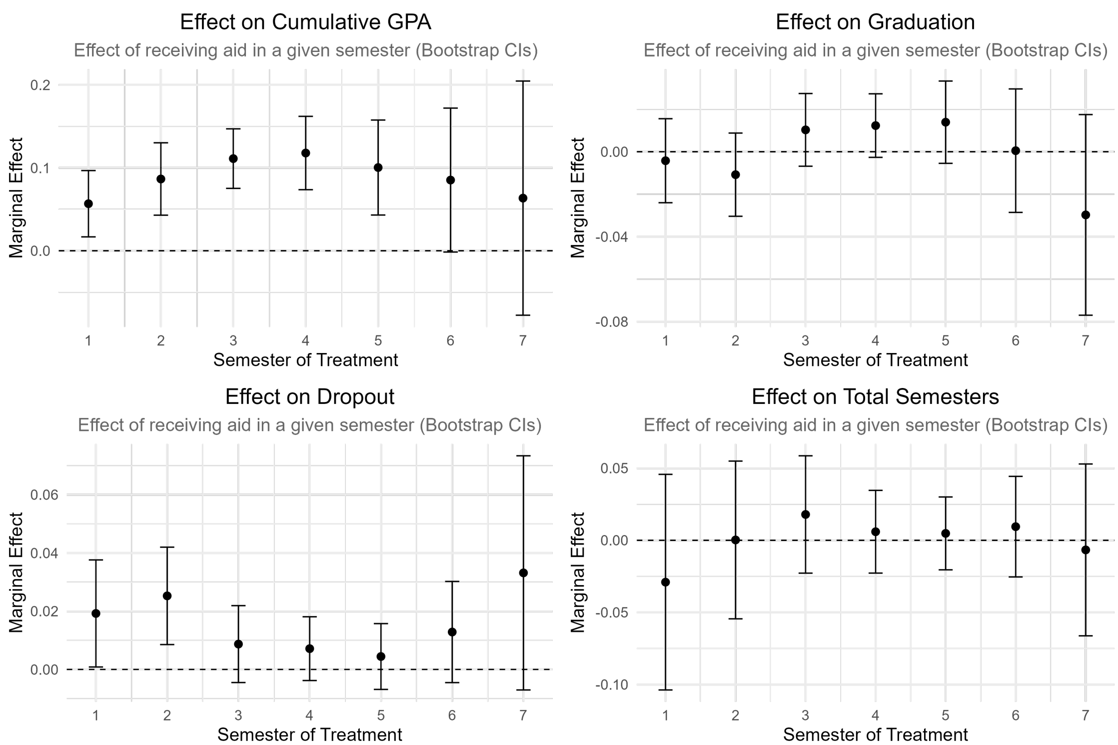
E Dynamic Decomposition Results for Stipends in RSU

Figure 24: Marginal Effect of Stipend Eligibility at a Given Semester with Delta Method SEs



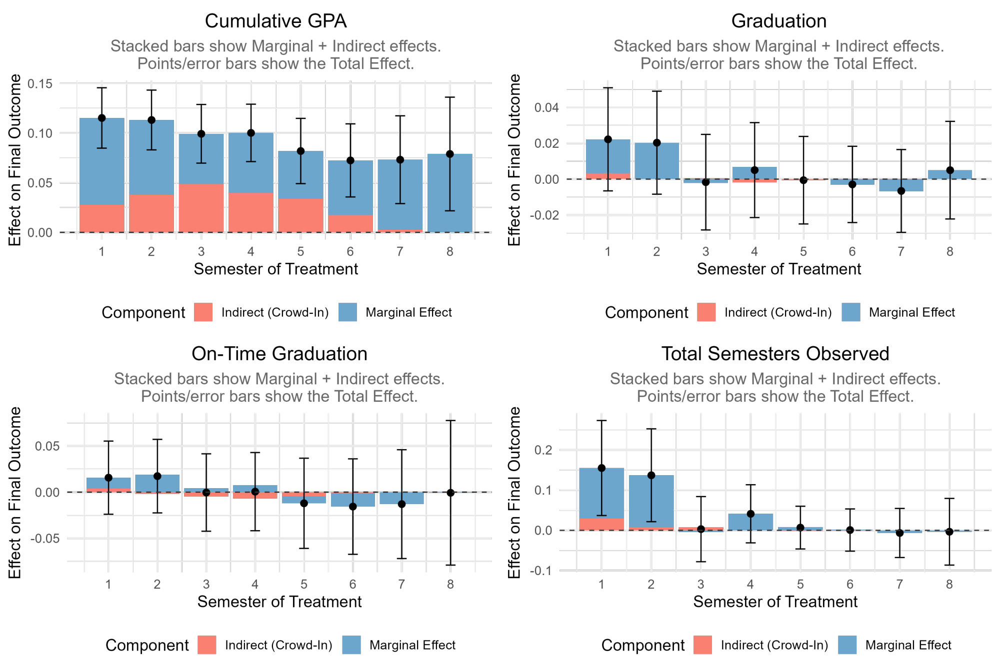
Note: The figures report the estimates from an indirect regression discontinuity decomposition on the marginal impact of being eligible for stipends in any given semester on a range of student outcomes. The estimation is done on students who start during the time period and whose expected graduation falls before the data horizon, and whose program length is 8 semesters.

Figure 25: Marginal Effect of Stipend Eligibility at a Given Semester with Bootstrapped SEs



Note: The figures report the estimates from an indirect regression discontinuity decomposition on the marginal, indirect, and total impact of being eligible for stipends in any given semester on a range of student outcomes. The estimation is done on students who start during the time period and whose expected graduation falls before the data horizon, and whose program length is 8 semesters.

Figure 26: Decomposition of Impact of Stipend Eligibility



Note: The figures report the estimates from an indirect regression discontinuity decomposition on the marginal, indirect, and total impact of being eligible for stipends in any given semester on a range of student outcomes. The estimation is done on students who start during the time period and whose expected graduation falls before the data horizon, and whose program length is 8 semesters.