Academic Accommodations in Higher Education: Patterns, Predictors, and Potential*

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November 29, 2025

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Abstract

The share of college students identifying as disabled and using academic accommodations (e.g., extended test time) has dramatically increased over the past two decades. We link course transcripts, disability office records, and K-12 special education histories at a large public flagship to study accommodations. We provide three main findings. First, we show usage has risen sharply—between 2011 and 2024, usage rose from 4% to 10%, driven by a fourfold increase in mental-health diagnoses. A decomposition exercise indicates K-12 disability growth explains about one-quarter of this increase. Second, we document stark socioeconomic disparities in use. Conditional on prior documented disability, men and Asian students are less likely to apply and be approved, and conditional on applying, high-income students are more likely to be approved. Third, using student fixed effects and comparisons between approved and non-approved applicants while controlling for rich observables, we find that accommodations yield substantial benefits. Approved students withdraw from fewer courses, earn higher GPAs, persist longer, and are more likely to major in STEM—driven by greater persistence among existing STEM students. Together, these findings clarify the sources of growth and gaps in use and provide some of the first evidence on the academic returns to accommodations in higher education, with direct implications for STEM diversity and retention.

*This research was funded with help from training grant R305B150012 from the U.S. Department of Education's Institute of Education Sciences. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not reflect the views of any other entity. This research used data structured and maintained by the MERI-Michigan Education Data Center (MEDC). MEDC data is modified for analysis purposes using rules governed by MEDC and are not identical to those data collected and maintained by the Michigan Department of Education (MDE) and/or Michigan's Center for Educational Performance and Information (CEPI). We thank staff at the study university disability office for generously sharing data and supporting this project and Kyle Kwaiser for support with data linkages. We thank Brian Jacob, Sara Heller, Katherine Michelmore, and Ben Scuderi for advising. We thank Matt Kraft, Michael Mueller-Smith, Charlie Brown, John Bound, Alexander Bolves, Zach Weingarten, Brittany Vasquez, Abigail Payne, Micah Baum, Annalise Paulson, Jack Mountjoy, Basit Zafar, Joshua Goodman, Marcus Winters, Mary Quiroga, Erin Gibson, Neil Christy, Ashley Walsh, and seminar participants at the University of Michigan and Midwest Economics of Education Conference for providing helpful feedback.

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1 Introduction

The number of college students identifying as disabled—and using academic accommodations like extended time for assignments, note-taking assistance, and audio/visual support—has grown dramatically in the last two decades.[1] Between 2004 and 2020, the share of undergraduates reporting a disability rose from 11% to 20% (Curda, 2024). Consequently, the share of students formally registered with their university's disability office—a proxy for accommodations usage—more than doubled from 3% to 7% in the last ten years. In 2024, approximately 1-1.3 million undergraduates received accommodations, making it one of the largest personalized interventions in higher education.[2]

Accommodations are intended to unlock students' potential—ensuring equal learning opportunities for students with disabilities by reducing barriers they face, such as inaccessible materials, environmental stressors, or rigid time constraints. By easing these burdens, accommodations should allow students to focus on learning the core material rather than struggling with the mode of delivery or evaluation. However, accommodations may not live up to their potential due to incomplete take-up, distributional effects, behavioral or strategic responses, and imperfect implementation. Usage among students with disabilities is incomplete—only one-in-four students who used accommodations in HS reported using them in college (Newman & Madaus, 2015). Usage skews toward higher-income students (Goldstein & Patel, 2019; Levinovitz, 2024; McGregor et al., 2016); in curved classes, gains for some students mechanically harm others. Accommodations may also incentivize some students to learn less if they can attain the same grade by devoting less effort to their accommodated courses and such supports may hinder the development of coping skills, harming later life outcomes. Lastly, implementation—including a student's ability to navigate the request process, a school's resources, and faculty cooperation—can impede the efficacy of accommodations.

Outside of anecdotal conversations, media reports, and small survey samples, we know surprisingly little about how many students use accommodations, why usage has increased, who uses them, or whether accommodations help students succeed. The main bottleneck is data. There

[1] In this paper, we use the word "disability" as it is used in the legal sense according to Section 504 of the 1973 Rehabilitation Act: any physical or mental impairment that significantly limits major life activities.

[2] Authors' calculations from IPEDS disability and enrollment data. IPEDS reports registration only when $\geq$3%, leaving $\sim$70% missing in 2024. We bound missing shares at 0–3%, multiply by school enrollment, and sum across schools—assuming registered students receive at least one accommodation.

are no national datasets that track accommodations usage, making it impossible to trace trends consistently or benchmark institutions. The Integrated Postsecondary Education Data System (IPEDS) provides only aggregated counts of disability-service registration and lacks demographic detail while using imperfect measures of disability status.[3] The National Center for Education Statistics conducts frequent surveys, but inconsistently asks questions about accommodations usage across surveys cycles, undermining comparability over time. Even when institutions gather their own data on accommodations usage, they rarely provide researchers with linked academic data to track how usage impacts subsequent academic achievement and course-taking. Links to K-12 disability histories are virtually nonexistent, as students arrive at colleges from across the country and institutions are legally restricted from asking about disability history,[4] leaving us unable to separate growth driven by changes in underlying need and K-12 processes from changes in campus processes. Without comprehensive, linked data, discussions around academic accommodations are shaped largely by speculation rather than systematic study.

This paper brings novel data to inform these discussions. We overcome many of the existing data limitations by linking three rich sources—university academic transcript data, disability office records, and in-state K-12 special education histories—at a large public flagship university. These linkages allow us to document long-run trends over a decade, measure sociodemographic gaps in use, and estimate the effects of accommodations on academic performance, persistence, course-taking, and field of study. Specifically, we ask the following research questions:

1. How has accommodations usage changed over time, and what explains this growth?

2. Who uses accommodations, who does not, and why?

3. What is the effect of accommodations on students' academic outcomes?

Although this study focuses on one institution, this university is representative of the universities that have seen the steepest increase in students receiving disability services (Weis & Bittner, 2022). In addition, almost half of students are in-state, enabling K-12 linkages that proxy underlying

[3]Students may be registered with their disability office but not using accommodations. In addition, schools report the share registered only if it exceeds 3%, so over half leave this field missing.

[4]Section 504 of the Rehabilitation Act of 1973 and Title II of the ADA prohibit differential treatment and unnecessary disclosure of disability status to third parties (U.S. Department of Education, Office for Civil Rights, 2008).

disability and academic preparation. This allows us to measure how K-12 disability prevalence contributes to growth in usage and gaps in use. The single-campus setting also provides granular, semester-by-semester measures of course-taking and grades. Most crucially, our setting is both large enough to precisely measure accommodations usage and diverse enough to study differences in use by gender, race/ethnicity, and family income.

We begin by developing a conceptual framework that explains how accommodations may improve learning, describes take-up decisions, and identifies the forces behind recent growth. We describe how accommodations usage may benefit students using Cognitive Load Theory (CLT): accommodations reduce *extraneous* load—time pressure, distractions, inaccessible formats—freeing cognitive capacity for learning. With these institutional guardrails, student academic performance should rise and they may opt into more demanding courses or majors, and they may be able to persist in these challenging pathways at a higher rate than before. We then consider accommodations access and usage, which involves a multi-stage process that includes awareness, application, approval, and course-level usage. In addition to underlying disability prevalence, frictions (informational, administrative, and social) can generate usage gaps by gender, race/ethnicity, and income. Finally, we consider growth: use rises when demand increases, supply expands (via improved institutional resources), and frictions fall (stigma and red tape). We use this framework to organize the analyses that follow.

First, we show usage has risen sharply in our study university—between 2011 and 2024, usage rose from 4% to 10%. All demographic groups see a similar rise in usage. We investigate possible drivers: rising disability prevalence and accommodations usage in K-12 (a pipeline effect), growing student demand, especially around mental health, and the supply of accommodations, the use of assistive technology in particular. We conduct a decomposition exercise and find rising K-12 disability rates account for only one-quarter of the growth. We find growth in usage is concentrated in mental health accommodations—which quadrupled during this time period—and the use of assistive technology and support services—which quintupled.

Second, although growth was uniform, there exist stark disparities in usage by gender, race, and income. Male and Asian students are roughly half as likely as female and white students, respectively, to ever use accommodations. Usage follows a "U-shaped" pattern by family income: students from middle-income ($50–200K) and high-income (>$200K) families are 30% and 10%

less likely, respectively, to ever use accommodations compared than their low-income (<$50K) peers. These gaps persist after conditioning on documented K-12 disability, suggesting they are not driven by differences in underlying disability rates. We show these gaps stem primarily from application behavior. Once we control for whether a student requests a meeting with the disability office, the gender and racial gaps largely vanish. Adjusting for application behavior reverses the relationship for income: high-income students are less likely to ever use accommodations (compared to low-income students) because they are less likely to apply for accommodations (15% vs 17%). However, once we condition on applying, high-income students are 7% more likely to be approved. This pattern is consistent with wealthier students valuing grades more, having greater underlying need, or navigating documentation and administrative hurdles more effectively.

Finally, we estimate the effect of accommodations on academic outcomes using two complementary designs. We first employ a student fixed effects model comparing outcomes before and after approval, the standard approach in the K-12 special education schooling literature (Hanushek et al., 2002; Hurwitz et al., 2020; Schwartz et al., 2021).[5] This removes time-invariant selection but faces two issues: (i) approval often follows downward pre-trends, which can understate effects if those trends would have continued or overstate them under mean reversion (Hanushek et al., 2002), and (ii) effects cannot be estimated for students who apply in their first semester, limiting generalizability. To address these issues, we use a second design that compares approved and non-approved applicants. Non-approvals largely reflect administrative frictions—missing documentation or missed appointments—rather than academic aptitude. We partially adjust for these channels using observed proxies and conduct extensive sensitivity and robustness tests to assess the magnitude of likely forms of omitted variable bias.

Accommodations offer immediate and substantial benefits. In the application semester, approved students are 4.2pp (71%) less likely to withdraw from the middle of the semester, withdraw from 0.2 (41%) fewer courses, and earn GPAs 0.1 points (3%) higher. Over the next three years, approved students show increased persistence—more enrolled semesters and credit hours—and they take more difficult and STEM courses. One year after approval, STEM majoring rises by 4pp (18%), driven mainly by greater persistence among existing engineering students rather than new

[5]A notable exception is Ballis and Heath (2021), which uses an instrumental variable strategy exploiting a policy change in Texas that required school districts to cap the share of students receiving special education services.

entrants. Because women are more likely to apply for and use accommodations than men, a useful benchmark is the female-male STEM gap—our results imply a 29% female-male STEM major gap closure three years after applying for accommodations, or over 100 additional women in STEM.

We show our results are robust to a broad set of sensitivity and robustness tests. This includes formal omitted variable bias sensitivity tests proposed by Xu et al. (2019), Frank et al. (2013), Altonji et al. (2005), and Oster, 2019. We also conduct checks to rule out specific forms of bias: including controls for documentation (a proxy for advantage) and unusually rich K-12 covariates that proxy for disability, preparedness, and family resources. We also use an alternative design—comparing students approved in the application term to those approved the following term due to administrative timing (e.g., processing and documentation delays)—and find similar results. Our results are consistent across differential attrition, eliminating compositional change concerns.

This paper contributes to several strands of research and public policy. First, we provide one of the most comprehensive descriptive accounts of accommodations use to date. Linking K-12 special education records, university disability data, and transcripts at a large flagship public university, we follow students across the accommodations pipeline and measure course-by-semester usage directly. This improves on prior work that has relied on IPEDS—which conflates disability registration with actual use and varies by institutional reporting practicesn(Weis & Bittner, 2022)—or on small, older surveys and interviews collected before the recent surge in usage (Adam & Warner-Griffin, 2022; Marshak et al., 2010; McGregor et al., 2016; Newman & Madaus, 2015). Our data let us track contemporary trends and document who uses accommodations and how that has changed.

Second, we clarify drivers of growth and access. Public discourse asks: why has usage grown, and who is driving it? We find growth is broad-based—not concentrated in any one demographic group. Rising K-12 disability rates account for only a quarter of the growth, and students with K-12 documented disabilities are less likely to use college accommodations today than they were fifteen years ago.he main engine is mental-health diagnoses, consistent with national trends. Importantly, we show growth in accommodations usage was evident prior to the COVID-19 pandemic, and has since accelerated. Regarding access, we document gaps in usage across gender, race, and family income, and show they arise almost entirely from application behavior. These results highlight a crucial angle in the equity debate: disparities in how students navigate the accommodations system.

Third, we provide new evidence on the effectiveness of accommodations and highlight methodological lessons for evaluating similar policies. Most prior studies—cross-sectional and survey-based—found little association between accommodations and outcomes (Los Santos et al., 2019; Newman et al., 2021).[6] The study closest to ours, Blasey et al. (2023), used student fixed effects and found similar GPA gains (0.05 points per semester). We advance the literature in three ways: (i) we show standard student fixed effects likely understate effects because approval often follows downward pre-trends (though mean reversion can bias upward if performance would have rebounded); (ii) we leverage comparisons among applicants—approved vs. not approved—providing a cleaner counterfactual; and (iii) we extend outcomes beyond grades to persistence, course difficulty, and major choice. Our results speak directly to STEM retention. Undergraduates with and without disabilities consider STEM at similar rates, but students with disabilities complete at lower rates (Carroll et al., 2020; Lee, 2011).Despite higher college entry, women are less likely to persist in STEM (Griffith, 2010; Reber & Smith, 2023). Stabilizing enrollment and performance via accommodations may be one lever for narrowing participation gaps.

Fourth, our work connects disability, human capital, and labor markets. People with disabilities face worse labor market outcomes than similar peers even at the same education levels.[7] Prior work has examined policy changes such as the ADA (Acemoglu & Angrist, 2001; Button et al., 2023) and minimum wage changes (Clemens et al., 2025), as well as providing accommodations once on the job (Anand & Sevak, 2017; Hill et al., 2016; Kruse et al., 2024; Maestas et al., 2019). This literature generally finds that workplace accommodations raise retention and labor supply but do not eliminate pay gaps. We add evidence earlier in the pipeline: a support service during college, a key period of human capital formation where decisions (e.g., major choice) are strongly linked to labor market outcomes.

Collectively, these contributions address long-standing gaps in the evidence base on accommodations in higher education. They also inform ongoing policy debates about equity and effectiveness: whether disparities reflect need or process barriers, what is fueling rapid growth, and how accommodations operate in practice. By grounding these questions in systematic evidence, this paper reframes the conversation and provides actionable insights for both researchers and practitioners.

[6]Freeman (2025) is an exception, that used administrative data in Texas community colleges and found accommodations usage was positively associated with completion rates for some disabilities but not others.

[7]In the 2021 SIPP, adults with disabilities and a BA+ are roughly twice as likely to experience unemployment and earn about 30% less per week than non-disabled peers.

2 Conceptual Framework

University disability offices grant academic accommodations with the purpose of removing disability-specific barriers. Accommodations can be approached through the lens of the social model of disability, which asserts students are disabled not solely by impairments but by an environment—such as rigid exam timing, inaccessible rooms or material, and distracting classrooms—that disproportionately affects disabled students (Shakespeare et al., 2006). Changing these conditions can level the playing field and allow students with disabilities to equally participate in learning. We develop a conceptual framework that begins with connecting cognitive load theory to student learning and the use of academic accommodations. We then consider channels that could explain the growth in accommodation usage and differences in usage rates among students.

2.1 How Academic Accommodations Work

Cognitive Load Theory provides a useful framework for describing how accommodations operate (Schnotz & Kürschner, 2007; Sweller, 1988). According to CLT, learning is constrained by limited working memory. Two pieces matter here: Intrinsic Cognitive Load (ICL)—the substance of the material—and Extraneous Cognitive Load (ECL)—features of delivery and assessment that siphon attention.[8] When ECL is high—because of distractions, time pressure, or inaccessible rooms and materials—students spend effort coping rather than learning. This high load impairs decision-making and task performance (Ball et al., 2023; Deck & Jahedi, 2015; Deck et al., 2021; Shiv & Fedorikhin, 1999). Students with disabilities face a higher ECL-to-ICL ratio than their peers. Consider the following examples: a noisy exam room for a student with ADHD, inaccessible PDFs for a low-vision student, a non-adjustable desk for a wheelchair user, or rigid deadlines for a student with chronic health needs. In each case, the environment—not the material—creates extra load.

Accommodations work by cutting ECL so more bandwidth goes to ICL. Extended time and reduced-distraction testing let students show what they know rather than what the format allows (Le Cunff et al., 2025). Benefits are largest where ECL is high and where the accommodation matches the barrier. They are smaller for students with already low ECL (e.g., a quiet room for a student who is not easily distracted). Many accommodations have both a general component (small

[8] A third term, germane cognitive load (cognitive activity supporting knowledge storage and later retrieval), is often grouped with ICL.

benefits for most students) and a disability-specific component (larger marginal benefits when the barrier aligns with the impairment). Match also varies by course: test-time helps in exam-heavy classes, less so in paper-only seminars. It is worth noting, as Ball et al. (2023) points out, "Cognitive load, which refers to the taxation of mental resources by a decision maker, is distinct from cognitive ability, which pertains to an absolute level of cognitive reasoning by the decision maker."

2.1.1 Implications

By lowering extraneous load, accommodations make learning and showing what you know less costly. Grades should rise and course withdrawals should fall where students face the highest ECL (e.g., timed exams). Because students take several classes and effort has diminishing returns within a class, freed bandwidth can have positive spillovers in courses students do not request or use accommodations for, lifting semester GPA.

Lowering these frictions also changes choices. By clearing gateway requirements and reducing format penalties, accommodations make it easier to persist in college, especially in fields with rigid assessments and dense problem sets (e.g., STEM). At the same time, expanded choice sets encourage some students to step into harder, higher-ECL coursework. The long-run net effect is therefore ambiguous: students may learn more yet keep similar GPAs if they climb the difficulty ladder; persistence may improve through choke-points yet fall later if the new bundle proves too challenging. Outcomes hinge on student–course match and the fit between supports and course demands.

2.2 Growth

Accommodations usage has expanded because of shifts in demand, supply, and frictions. On the demand side, underlying disability and needs have increased. The disability prevalence among the population, both children and adults, has risen over the past decade, from 12% in 2011 to 13% in 2021 (Erickson et al., 2025). Mental-health service use among U.S. adults rose from 13.6% to 18.8% over the same period, as well as rates of youth anxiety and depression (Lebrun-Harris et al., 2022; Substance Abuse and Mental Health Services Administration, 2012, 2022). Although COVID may have exacerbated trends, there was an upward swing prior to COVID (Lebrun-Harris et al., 2022). The K-12 disability pipeline expanded too. The share of K-12 students with disabilities—

those served under the Individuals with Disabilities Education Act (IDEA) and Section 504 of the Rehabilitation Act of 1973—rose from 13% to 17% between 2000 and 2020 (U.S. Department of Education, 2024), and College Board (SAT) accommodation requests increased by 200% between 2010 and 2018 even as test-takers rose only 25% (Belkin et al., 2019).[9] More students arrive at postsecondary institutions with needs and prior exposure to supports than ever before.

On the supply side, supports have evolved. Assistive technologies (captioning, lecture capture, alternative file formats, screen readers) and proctoring/testing capacity have lower delivery costs and are more scalable today because of technological advancements. Years after the pandemic, colleges continue to see more online courses, fewer face-to-face courses, and increasing use of digital-based learning tools and web accessibility (Donadel, 2023; Mowreader, 2025). Many disability offices have shifted from paper to online case-management systems (e.g., Accommodate) that streamline scheduling, documentation uploads, and instructor notifications.

Third, classic take-up frictions have fallen. Students may not accept accommodations despite needing them due to stigma of receipt, program participation costs, imperfect information, and administrative barriers (Ko & Moffitt, 2024). To obtain academic accommodations, the student must self-disclose their disability to the office and, upon approval, have their disability needs exposed to the professor and potentially classmates. As more students use accommodations and mental health stigma has fallen, so too have stigma-induced costs. One of the major costs involved in getting accommodations is documentation. Documentation norms have shifted—instead of accepting only external, objective records, disability offices are increasingly prioritizing student self-reports (Greenberg, 2022; on Higher Education & Disability, 2012).

2.3 Access

Who gets accommodations depends on underlying rates of disabilities and where frictions remain. On average, non-white children report higher rates of disability than white children; however, Asian children report the lowest incidence of disability (Young & Crankshaw, 2021).[10] Children living at or below the poverty line are more likely to have a disability than children living above the poverty

[9]This trend reflects both increases in disability-induced demand as well as increases in competition for grades and spots in selective colleges.

[10]According to the ACS,in 2019 non-Hispanic Black and American Indian and Alaska Native children reported rates of disability at 5.1% and 5.9%, respectively, compared to 4.3 % of non-Hispanic White and Hispanic children and 2.3% for Asian children (Young & Crankshaw, 2021).

line (6.5% and 3.8%). The prevalence of disabilities also differ by sex. For instance, boys are twice as likely than girls to have a developmental disability, such as autism spectrum disorder, intellectual disability, or any other developmental delay (Zablotsky et al., 2023). On the other hand, girls are 30-45% more likely than boys to be diagnosed with anxiety or depression (Wang et al., 2025).

Documentation and time costs loom large. For example, ADHD assessments can run $200–2,000 (and far more for full neuropsych evaluations), require multiple visits, and face uneven insurance coverage (Center, 2025; Pedersen, 2025). Students without time, money, or help struggle to assemble documentation. Prior K-12 plans and strong advising lower these costs, which helps students from higher-SES schools where K-12 accommodations growth has been steepest (Goldstein & Patel, 2019).

Stigma and help-seeking norms create gaps even conditional on eligibility. Men are less likely to request supports even when eligible (Angrist et al., 2009); adolescent boys and Black/Asian youth seek help less often conditional on need (Sen, 2004). Cultural attitudes toward disclosure and mental health can depress applications for some Asian-origin students (Nguyen et al., 2024). Evaluators also report greater skepticism for less visible conditions (e.g., ADHD) (Lindsay et al., 2018; Marshak et al., 2010; Pfeifer et al., 2021).

Finally, course environments are not neutral: students facing higher extraneous load in timed, test-heavy, or STEM settings have more to gain, so usage will concentrate there—even holding baseline need fixed.

3 Background

3.1 Disability in the Education System

To understand how accommodations usage works in college, it is helpful to describe how disability services work in K-12 first. There are major policy differences in disability law in the U.S. that make students' K-12 disjointed from their college experiences. These differences may influence the take-up and impact of accommodations in college. In K-12, students are supported by the IDEA and Section 504 of the Rehabilitation Act of 1973. IDEA covers children ages 3 to high school graduation and applies to 13 specific disability classifications, while Section 504 covers people of all ages and uses a broader definition of disability (see Table A1 for details and examples of disabilities).[11] Under IDEA, K-12 schools must create individualized education plans (IEPs) for eligible students, providing individualized instruction and support. Section 504 plans, while not providing individualized instruction, ensure students have equitable learning environments through academic accommodations like extended test time. K-12 schools are responsible for identifying students, conducting evaluations, and providing supports.

In higher education, however, the responsibility shifts to the student. IDEA does not apply for postsecondary education, but Section 504 does, allowing eligible students to receive accommodations, such as extended test time, though not individualized instruction. Students must register with their institution's disability services office to receive accommodations. They must proactively locate the office that provides disability services, identify themselves, request accommodations, and provide the necessary documentation.

This shift in responsibility lowers the likelihood that students identify as disabled and obtain accommodations in college. In national surveys, about two-thirds of students who reported having a disability in high school did not report having one in college (Adam & Warner-Griffin, 2022). This may reflect true changes in condition or changes in self-identification. Either way, it depresses postsecondary accommodations use: among high school students who used accommodations, only one in four used them in college (Newman & Madaus, 2015).

3.2 Disability Services At The Study University

At the study institution, students seeking academic accommodations must navigate a structured, multi-step process coordinated by the university's disability services office through an online platform called Accommodate. The university began using this system in Fall 2021.

The process begins when a student completes an online intake form on Accommodate. About 14% of the students in our study university are observed in this system. Students provide basic information on their disability, functional limitations, and requested accommodations. Students are encouraged to upload documentation at this stage (about half do), although it is not strictly required prior to scheduling a meeting. Documentation typically includes medical records or evaluations.

[11] The IDEA generally applies to public school students, though private school students may receive some services at the discretion of the public school district where they reside. Section 504 applies to any school receiving federal funding, including from student lunch programs or student loans. The American with Disabilities Act (ADA) extends the same protections from Section 504 to private institutions; in practice, almost all universities receive federal funds either directly or indirectly through student loans, making them subject to both Section 504 and ADA requirements.

After submitting the intake form, students are prompted to schedule an initial "welcome meeting" with a disability services coordinator. These meetings typically occur within two weeks of the initial request. Among those applying, 96% are observed meeting with their coordinator.[12] During the meeting, the coordinator and student discuss the student's educational history, current challenges, and goals for accommodations. The coordinator uses this information, combined with any submitted documentation, to determine which accommodations are reasonable and legally appropriate.

Following the intake meeting, the coordinator either approves accommodations directly—common for standard supports like extended testing time—or refers the case for team review if the request is atypical. Team reviews ensure consistency across coordinators and compliance with Section 504 of the Rehabilitation Act and the Americans with Disabilities Act. Approved accommodations are then entered into the Accommodate system. Approximately 73% of students are approved in the semester they apply.

Approval does not automatically trigger accommodations each term. Instead, students must log into Accommodate at the start of each semester and select the courses for which they want accommodations. The system then sends notifications directly to faculty, eliminating the need for students to hand-deliver letters or disclose their disability in person. This automated process was designed to reduce stigma and standardize communication with instructors.

Not all students who initiate the process ultimately receive accommodations. The most common reasons are failure to complete required steps, such as missing the intake or follow-up meeting or not submitting documentation. Among students who are observed meeting with their coordinator, 81% are approved, while only 30% of students who do not meet with their coordinator are approved.[13] Among students who submit documentation during the initial meeting request, 81% are approved, while 71% of those who did not initially submit documentation are approved.[14] Students can also be denied if they request accommodations deemed inappropriate for their documented disability.

[12] A student is considered meeting with their coordinator if the number of welcome meetings a student requests is greater than or equal to the number of non-canceled welcome meetings. Coordinators may not always flag a meeting as canceled, especially if cancellations are last minute, so this is an upper bound.

[13] This number is greater than 0% because, as described above, we have an imperfect measure of meeting with a disability coordinator. In addition, during busy weeks and late in the semester, the office automatically grants students accommodations conditional on scheduling a meeting. This is to ensure students receive accommodations in a timely fashion.

[14] We only observe if a student submitted documentation with their intake form and do not observe if documentation was submitted afterwards.

In such cases, students may submit additional documentation, request reconsideration, or file an appeal.

4 Data and Sample

We combine three datasets: (1) administrative transcript data from a large flagship public university, (2) accommodations data from the disability office of this university, and (3) administrative K-12 records for students who attended in-state public high schools. The transcript data contain information on the universe of students from the university. These data are at the student x semester x course observation level and include details on enrollment and graduation, course selection, grades, and major choice. We also observe whether students withdraw from courses or the semester if they formally registered for courses. The data also have information on student characteristics, including gender, race, high school background (GPA, Advanced Placement courses, and standardized test scores), and household income.[15]

The academic accommodations data, provided by the disability office, come from two main sources. The first is through the above described Accommodate system. The data contain detailed information on when students requested meetings with disability coordinators (and the coordinator they were assigned to or met with), when and if they received accommodations, and what accommodation they received (e.g., extra test time vs note-taking support). We also observe if students requested accommodations in a specific semesters and the specific courses they requested them for. The data also classify the types of disabilities students have, as noted by the student's disability coordinator. We use a combination of large language models and simple text categorization to group disabilities and accommodations into tractable categories. These data are available from the Fall 2021 semester to the Winter 2025 semester.

The second disability dataset is sourced from the rosters of enrolled students with accommodations used by the office to compile annual reports. These data are available for the following

[15] Students self-report household income at the time of application, and it is coded into four categories: \$0-50K, \$50-100K, \$100-200K, and \$200K+. This variable has a high missing rate (37%) because students in our data come from high SES backgrounds, so many do not report household income with the understanding they are unlikely to receive needs-based grants. We deal with the missingness by imputing missing values using the median household income in their HS neighborhood using data from the Stanford Education Data Archive and by including a missing indicator whenever this variable is used in analyses (Reardon et al., 2024).

academic years: 2011-12, 2014-18. These files contain student-level records indicating when a student was first approved, what accommodations they received, and their reported disability. These data are less detailed than the Accommodate data, but they allow us to trace trends in usage.

We combine these university data with administrative K-12 records for students who attended in-state public schools, which is approximately half of our sample. We observe if a student had an IEP or 504 plan in K-12, when they received these services, and the type of disability reported (for IEP students). We consider a student as having a documented disability in K-12 if they had an IEP or 504 plan in high school (grades 9-12). The dataset also includes information typical of K-12 administrative datasets: student demographics, performance in standardized tests, disciplinary data, and information about the high schools students attended. These data allow us to trace the disability pipeline from K-12 to post-secondary.

4.1 Sample

We make a small number of sample restrictions. We restrict our sample to undergraduate students. Because our accommodations data snapshots are incomplete prior to Fall 2021, we restrict most of our analyses to using data from Fall 2021-Winter 2025, except when examining trends over time, where we use the full sample from 2011-2025. Our main analytic sample consists of five academic years of data for over 60,000 undergraduates (over 200,000 student x semester observations).

We present summary statistics for students in our sample in Table A2. A sizable share of students ever submit an intake form and request a meeting with the disability office (14%) and are ever observed using accommodations (10%). The school has a large number of Asian students (25%) and high achieving students (SAT scores over the 95th percentile). Most students—almost half—are originally accepted into the school of arts and sciences, followed by engineering (15%), and business (6%). In Table A3, we compare our institution to other institutions using IPEDS data. The institution we study is larger and more expensive than many other public and selective schools. It also has fewer black and Hispanic students and more Asian and high-performing students as measured by standardized test scores.

Although different from the typical university, the current institution under study is a good context for evaluating the role of academic accommodations for several reasons. First, it is representative of the selective schools that have seen the steepest growth in students who registered for disability services (Weis & Bittner, 2022). Second, it is large (30,000 undergraduates enrolled annually) and over half of the undergraduates come from the state of the university, so data linkages to K-12 systems are possible. The university also has a sizable disabled student population, among one of the highest of the state's four-year institutions. This combination of size and the large share of students with disabilities will increase the odds of detecting a precise effect of accommodations if there is one. Finally, attending selective institutions like the university under study has been shown to produce greater benefits for students such as higher graduation rates and earnings (Lovenheim & Smith, 2023), so students with disabilities stand to benefit a great deal.

4.2 Disabilities and Accommodations

We summarize the types of disabilities and accommodations students receive in Table 1. Approximately 96% of students with accommodations report having just one or two different types of disabilities. The vast majority of accommodated students report a learning disability like ADHD (52%) and mental health issues like anxiety or depression (47%), and 80% have either.

Approved accommodations are similarly concentrated. Students receive about two accommodation types on average. Almost all accommodated students receive some sort of testing accommodation like extended time (93%). One-third of approved students receive accommodations for assistive technologies and support services like screen readers and voice-to-text software.

5 Trends in Accommodations Usage

We analyze trends in accommodations usage over the past decade using longitudinal data. To assess what drives growth, we compare student cohorts and conduct an Oaxaca-Blinder decomposition. This lets us quantify how changes in student composition—such as rising K-12 disability prevalence—contribute to increases in accommodations usage

Usage of academic accommodations has surged over the past decade. In Fall 2011, only 4% of enrolled students were approved for accommodations; by Fall 2024, that share exceeded 10%, echoing national patterns (Figure 1). This is 9% greater than what we would expect given the pre-COVID trend, suggesting a post-pandemic effect.[16] In Figure A1, we compare usage rates across

[16] Note that data in Fall 2021 are incomplete as the university was transitioning into using the Accommodate system.

cohorts, and show this increase in usage is not due to any one demographic group. For example, usage rose by 196% for international students, 128% for out-of-state students, and 172% for in-state students.

This raises a central question: why has usage grown so quickly? As described in our conceptual framework, three forces likely contribute: (i) growing student demand for support, particularly around mental health and in the pipeline of students arriving with documented disabilities in K-12, (ii) shifts in the supply of accommodations, (iii) falling frictions (e.g., stigma).

Our data allow us to speak directly to (i) and (ii), but not (iii). Institutional supply-side changes that affect usage frictions, such as expanded disability office staffing, streamlined intake processes, or proactive outreach could reduce barriers to approval and explain part of the increase; however, we lack direct measures of these changes over time and treat them here as a residual factor captured in the "unexplained" portion of our decomposition exercise.

5.1 Demand: Pipeline of Rising Disability Identification in K-12

Rising disability identification in K-12 might help explain these trends. Nationally, the share of students with IEPs rose from 11% to 14% between 2010 and 2021, while 504 plans tripled from 1% to 3% (Figure A2). These trends are even more pronounced in the high schools the students in our sample attended. If more students arrive at college with prior plans, rising usage in college could simply reflect a pipeline effect.

We test this hypothesis using our sample of in-state students, where we observe prior documented disability. Two facts complicate the pipeline explanation. First, even amid rising K-12 identification, most students at our university never had formal plans. By Fall 2024, fewer than 4% of in-state students had a 504 plan in high school (panel A of Figure 2). While the share of accommodated students with 504 plans has increased over time, in 2024 only one-quarter of in-state students with accommodations had a documented disability history in K-12 (panel B of Figure 2). Second, accommodations usage rates among students with K-12 plans have actually fallen: among students with HS 504 plans, the share using accommodations in college declined from 77% to 70% between 2011 and 2021 (Figure A3). Meanwhile, usage doubled among students with no documented high school disability. These patterns imply that the K-12 pipeline explains only part of the growth.

To quantify the role of compositional changes versus institutional factors, we use a Oaxaca–Blinder decomposition on in-state students, for whom we observe K-12 disability histories. This approach breaks down the difference in average outcomes between two groups into parts that are "explained" by observable differences in characteristics and parts that are "unexplained" due to differences in how those characteristics relate to the outcome. This allows us to answer, for example, how much did changes in 504 rates in K-12 contribute to changes in accommodations rates in college? Although not a causal method, it offers a useful accounting exercise to quantify which factors are most associated with changes in usage over time. See Appendix B for details.

Figure 3 summarizes the results. Between the 2011 and 2021 cohorts, the percent of students ever using accommodations increased from 4.8% to 13.2% (about 8.4 pp).[17] Roughly one-quarter of the increase is explained by changes in observables—driven almost entirely by higher K-12 IEP/504 prevalence. The remaining three-quarters is unexplained by observables, which can include shifts in demand, diagnosis mix, or institutional practices.

5.2 Demand: Changing Student Needs

Beyond compositional shifts, student demand for accommodations has fundamentally changed. Mental health conditions, in particular, have become far more prevalent. In Fall 2011, 2.4% of students were approved for a learning disability and 1.2% for a mental health condition. By Fall 2024, those shares rose to 5.4% and 5.0%, respectively (Figure 4A). This means reports of learning disabilities roughly doubled, while mental health approvals quadrupled (Figure 4B).

Is this campus-specific or part of a broader trend? We cannot observe population disability directly among students in our data (we only see disability status for approved students), and there is no national administrative dataset on accommodations. As a proxy, we compare our mental health approvals to self-reported mental health among a nationally representative sample of college students from the National Postsecondary Student Aid Study (NPSAS). If take-up conditional on having a condition is roughly stable over time, parallel growth across these series is informative.

Figure A4 shows that from 2011 to 2019 the NPSAS share reporting a mental health condition nearly tripled (3.4% to 9.9%), and our university's mental-health-related approvals also roughly

[17] These are different than the trends numbers described above because they are "life-time usage" rather than point-in-time measures.

tripled over the same window.[18] This alignment suggests the rise we document reflects a national shift rather than a campus anomaly. The pattern predates COVID, with the pandemic likely amplifying an existing upward trend.

5.3 Supply: Changes in Accommodations Provided

What colleges provide has changed alongside demand. Figure 5 shows trends in approved accommodations. Test-taking supports remain the modal service—over 90% of approved students receive some testing accommodation—but the fastest growth is in assistive technologies and broader supports (note-taking software, audio/visual tools, laptops). From Fall 2014 to Fall 2024, the share receiving testing accommodations roughly doubled (2.4×), while assistive tech and support services grew more than fivefold (5.5×). Advances in educational technology and the digitization of classrooms have made supports like screen readers, captioning, and shared lecture recordings both feasible and widely available in ways they were not a decade ago.

In sum, rising K-12 disability rates explain a small share of the increase in accommodations usage. The larger story appears to be evolving student needs—particularly around mental health—and the types of supports universities provide. These findings set up the next part of the paper, where we examine who accesses accommodations today and whether they achieve the intended goal of improving academic opportunities.

6 Who Uses Accommodations, Who Does Not, and Why?

Understanding which students access accommodations clarifies drivers of usage gaps. If gaps arise because some groups have higher disability prevalence (e.g., women are more likely to report having anxiety and depression), then higher usage among those groups simply reflects differences in need rather than unequal access. If gaps emerge because certain groups are less likely to apply or are less likely to be approved despite similar needs, this signals there are barriers in the accommodations process itself. This distinction guides our analysis; we are able to distinguish between gaps arising from documented disability from those stemming from application and approval behavior with our

[18] We lack campus accommodations data for 2019, so we linearly interpolate between 2017 and 2022.

sample of in-state students.[19] This provides insights into where college disability services may inadvertently reinforce inequalities and where reforms in outreach, advising, or approval processes could close those gaps.

For this analysis, and the remainder of the paper, we focus on students enrolled between Fall 2021 and Winter 2025. This period is unique in that we observe detailed disability histories from K-12, application behavior, and approvals.

6.1 Predictors of accommodations usage

We begin by highlighting broad demographic patterns in usage in Table 2, where we regress a binary indicator of ever using accommodations on student characteristics.[20] We find that gender and race are strongly predictive of accommodations usage. Focusing first on out-of-state students (column 1), we show that women are 41% more likely to use accommodations than men. Asian and black students are 64% and 48% less likely to use accommodations than white students.

We also find differences in accommodations usage by household income and prior student achievement. There is a "U-shaped" relationship between household income and accommodations use. Students from middle-income backgrounds (household income between $50-200K) are 22-24% less likely to use accommodations compared to their low-income peers. In contrast, high-income students are just as likely to use accommodations compared to their low-income peers. We also find that students with a strong HS background—as measured by HS GPA and total AP classes taken—are less likely to use accommodations. At the same time, students who performed better on standardized tests are more likely to use accommodations. In column 2, we repeat this exercise among in-state students and find qualitatively similar results, though the point estimate on black attenuates and is only marginally significant, and the point estimate on high-income increase in magnitude—these students are 13% less likely to use accommodations compared to low-income students. These differences likely reflect systemic differences between in-state and out-of-state students. We will focus on these in-state students for the rest of our analyses in this section.

[19] We acknowledge that this measure of prior disability is limited because students may have disability-related needs but may not have received an IEP or 504 plan in K-12. If K-12 take-up is related to gender, race, and SES, we may over-or-under-estimate the role of prior disability and application behavior. However, given the legal mandate K-12 schools have to identify students with disabilities, we believe this is an adequate measure of prior disability.

[20] See Table A4 for raw descriptives.

6.2 Decomposing the Gaps: Prior Disability and Application Behavior

The demographic gaps documented above raise a natural question: do they reflect differences in disability prevalence, or disparities in who applies for and receives accommodations once on campus? To answer this, we use linked K-12 data available for in-state students, which includes information on whether a student had an IEP or 504 plan in high school. Having such plans reflect both disability prevalence and access to supports in HS.

Adding prior disability status to the model in column 3 substantially increases explanatory power—the R^2 almost triples. The coefficient on the indicator is large and highly significant—students with an IEP or 504 plan are five times more likely to use accommodations in college than students without them. Yet the gender gap remains unchanged and the Asian–white gap narrows only modestly (from –4.5pp to –3.5pp). This suggests that differences in prior documented disability explain little of the gender gap and only about 20% of the Asian–white gap. In other words, high usage rates among women and white students are not a result of a greater prevalence of documented disability in K-12.

In column 4, we consider the role of application behavior using an indicator for whether a student met with the disability office.[21] This variable is highly predictive of accommodations usage—69% of students who apply are approved. Strikingly, controlling for application behavior nearly eliminates the gender and racial gaps. This suggests disparities arise because men and Asian students are far less likely to seek support in the first place (7% of Asian students request meetings versus 16% of white students; 10% of men versus 17% of women).[22]

Family income patterns also shift. Before conditioning on application, low-income and high-income students are about just as likely to use accommodations. After conditioning, high-income students are 7% more likely to be approved than low-income students. This may reflect differences

[21] We code a student as having applied if they appear in the Accommodate appointment data. It is possible that students may have requested a meeting with a coordinator without any intention to receive academic accommodations (e.g., for housing support or a parking pass); however, from discussions with disability coordinators, these account for a negligible share of appointments. If such cases are included in our measure of appointment request, we would slightly underestimate the share of the difference attributable to application behavior.

[22] Two margins can generate these application gaps: (i) differences in disability prevalence and (ii) differences in application rates conditional on disability. In Table A5, we examine the gender-gap and Asian-White gap within students who did or did not have an IEP/504 plan in HS. Among students having an IEP/504 plan, controlling for application behavior eliminates 60% of the gender-gap in usage, suggesting this gap is not driven by differences in disability prevalence. We are unable to draw conclusions for the Asian-White gap given the small number of Asian students with IEP/504 plans resulting in noisy point estimates.

in obtaining documentation; for example, psychological testing is costly and wait times at university health services can be long. It may also reflect differences in students' experience or capacity to navigate higher education bureaucracy.

We observe whether students submitted documentation at the time of application—about half do—but including it in our model (column 5) does not eliminate the high-income approval advantage. Using more granular measures of documentation—external medical provider, university provider, K-12, and other—in column 6 also has no effect. Moreover, the coefficient on first-gen status remains negative, stable, and statistically significant across both models (-0.006) and is almost the exact size as the coefficient on high-income students (+0.007). This suggests that wealthier students may value grades more, have greater underlying need, or navigate administrative hurdles more effectively, possibly through parental advocacy or higher quality documentation we do not observe (e.g., medical specialists).[23]

In sum, accommodations usage is patterned, but not in ways commonly assumed. Contrary to narratives of affluent overuse, low-income students are slightly overrepresented among users. Gender and racial gaps in usage stem primarily from application behavior, while income differences come from approval processes. These findings suggest that these differences in use arise less from differences in need and more from differences in navigating the accommodations system.

7 Effect of Accommodations on Student Outcomes

In our framework, students with disabilities face greater ECL and accommodations lower ECL. Our estimand of interest is the causal effect of accommodations approval on academic outcomes. Let $Y_{it}(a)$ denote student i's outcome in term t if (counterfactually) they are *approved* ($a = 1$) or not ($a = 0$). The parameter of interest is

$$\beta \equiv \mathbb{E}[\, Y_{it}(1) - Y_{it}(0) \mid i \in \mathcal{A}\,],$$

[23]These results are suggestive as we do not observe if a student submitted documentation after the time of application. It is possible that students submitted documentation at a later date—this would attenuate the explanatory power of the documentation variable.

the average effect among applicants $\mathcal{A}$. Heterogeneity in β is expected because students differ in disability type, the bundle of approved supports, and the ECL of their course portfolio.[24] We estimate this target using two complementary empirical approaches: (i) a student fixed effects model comparing outcomes before and after accommodations approval and (ii) a cross-sectional comparison of approved and unapproved applicants among students who apply, leveraging rich controls to adjust for observables.

7.1 Student Fixed Effects

We begin with a student fixed model, which leverages within-student changes in outcomes over time. This approach is widely used in education research to estimate the effects of individualized supports such as special education in K-12 settings (Hanushek et al., 2002; Hurwitz et al., 2020; Schwartz et al., 2021), and has also been applied in recent work on accommodations in higher education (Blasey et al., 2023; Chiu et al., 2019).[25] We restrict our sample to first-time applicants and only include observations up to the semester of application for short-term outcomes. Formally, we estimate the following model:

$$Y_{it} = \alpha + \widehat{\beta}_{\mathrm{FE}} Approved_{it} + Student_i + Semester_t \times Cohort_i + \epsilon_{it} \tag{1}$$

Here, Y_{it} is the outcome (e.g., GPA) for student i in semester t. The treatment, $Approved_{it}$, is a binary indicator that is equal to one if a student is approved for accommodations in a semester. We include student fixed effects ($Student_i$), which adjust for time-invariant student characteristics, such as gender, SES, and academic aptitude. We also control for semester of application x college entry cohort fixed effects ($Semester_t \times Cohort_i$) to adjust for common time shocks affecting all students in a cohort. ϵ_{it} is the error term. Our coefficient of interest, $\widehat{\beta}_{\mathrm{FE}}$, is the average difference in a student's outcome before and after accommodations approval.

Threats To Identification. To interpret $\widehat{\beta}_{\mathrm{FE}}$ as causal ($\widehat{\beta}_{\mathrm{FE}} = \beta$), we must assume that—conditional on student and cohort-by-semester FE— accommodations take-up is uncorrelated with

[24] Our estimators average over this heterogeneity

[25] Chiu et al. (2019) specifically looks at the difference in outcomes for students getting accommodations earlier vs later in their college career and Blasey et al. (2023) looks at the impact of cumulative semesters of accommodations use on student outcomes.

time-varying unobservables that affect outcomes, or the decision to apply for and use accommodations is as good as random. This precludes scenarios such as: a student picking up accommodations in conjunction with a sudden health shock, a string of poor academic performances, or starting medication that may improve outcomes. Such scenarios would bias $\widehat{\beta}_{\text{FE}}$ and conflate the effect of these events with the effect of accommodations.

We also highlight two related limitations of this approach, which are often underappreciated but particularly relevant in our context. First, consider the scenario of declining pre-treatment trends.[26] Suppose students apply for accommodations after several semesters of falling grades. Even if the decision to seek accommodations is not caused by these declines, their pre-treatment outcomes will exhibit a downward trajectory. As a result, post-treatment outcomes may appear only modestly better—despite a potentially large causal effect—simply because they are being compared to an unusually high baseline resulting from a declining secular trend. In this case, $\widehat{\beta}_{\text{FE}}$ would be biased downward, conflating genuine improvements with a reversal of pre-existing trends.[27] We address this limitation by adjusting for the pre-treatment trend. Specifically, we (i) average pre-treatment point estimates and (ii) subtract all time period estimates by this pre-treatment mean to estimate the effect of accommodations under the assumption that the pre-treatment trend would have continued in the absence of treatment.

The second limitation is that student FE models require students to have pre-treatment observations for identification. This means we cannot identify effects for students who receive accommodations in their first semester of college—approximately 40% of students who receive accommodations—because they are "always treated". Treatment effect estimates are therefore local to students who delay take-up or select into treatment later and may not generalize to early users.

Despite these limitations, this approach is a useful starting point. It controls for all time-invariant student characteristics and yields interpretable estimates of within-student change in outcomes, avoiding many of the biases in cross-sectional comparisons.

[26] Hanushek et al. (2002) highlight this concern in the K-12 setting.

[27] Mean reversion could, in theory, inflate effects if outcomes rebound after a low for reasons unrelated to approval. This requires the rebound to line up exactly with approval timing (e.g., simultaneous medication or new supports) independent of accommodations. In this case, we would bias post-period estimates upward and conflate the effect of accommodations with other supports.

7.2 Approved vs. Not Approved

We complement the student FE model by using our sample of applicants, comparing the academic performance among students in the same cohort who applied for accommodations in the same semester, contrasting those who were approved from those who were not. We restrict our dataset to a cross-sectional sample that consists of one observation per student in the semester in which each student first requested a welcome meeting with the disability office. Our goal is to estimate the effect of receiving accommodations approval on student outcomes at the point of initial application, after any negative or positive shock.

We estimate the following regression:

$$Y_i = \alpha + \widehat{\beta}_{\text{App}} Approved_i + X_i + Cohort_i \times Semester_t + \epsilon_i \tag{2}$$

where $Approved_i$ is an indicator equal to one if student i was approved for accommodations in the first semester they applied.[28] The vector X_i includes rich student-level controls: gender, race, household income, high school GPA, SAT scores, and number of AP classes. For some analyses, we also include pre-treatment college-level controls such as lagged cumulative GPA, lagged indicators for athlete status and major declared, major type, and home college (Arts & Sciences, Business, Engineering). These covariates aim to address observable confounding, particularly given that approval may be correlated with academic ability and socioeconomic status. We also include a college entry cohort x semester of application fixed effect ($Cohort_i \times Semester_t$), which restricts our estimation to comparisons between students of the same cohort applying in the same semester. This adjusts for the fact that students in the same cohort applying at different times in their college career are different in unobservable ways that may be correlated with performance (e.g., we do not want to compare a junior experiencing a negative health shock to a freshman applying for accommodations in their first semester).

[28] Approximately one-quarter of students applied in a semester in which they were not enrolled (e.g., applying a week before the beginning of the semester they are enrolled). As a result, we also include an indicator for applying in a non-enrolled semester. Results are similar if these students are excluded.

Threats to Identification. The main source of bias with this strategy is that approval is not random. We showed above that, conditional on applying, high-income student are more likely to be approved. If such students are higher-performing and better able to secure necessary documentation or evaluations, then our estimation strategy will overstate the true effect of accommodations ($\widehat{\beta}_{\text{App}} > \beta$). We test for this by regressing approval status on baseline covariates and find small but detectable socioeconomic differences in approval rates: students who are approved have, on average, a HS GPA that is 0.14 points (4%) greater and a 0.01 SD higher SAT score.[29] In so far as observable characteristics like race, SES, and HS performance are correlated with accommodations approval and student academic performance, including them in our regression models will mitigate bias. We detail other strategies to combat omitted variable bias in section 7.5.3.

7.3 $\widehat{\boldsymbol{\beta}}_{\textbf{FE}}$ vs. $\widehat{\boldsymbol{\beta}}_{\textbf{App}}$

Although these two estimation techniques attempt to uncover the same underlying estimand, they can produce different estimates for at least two reasons. First, consider sampling variation. The FE sample excludes first-semester adopters, while the applicant design targets all first-time applicants. First-semester applicants have a different composition of disabilities than other-semester applicant, and if disability type is correlated with academic ability, dropping these students will limit the generalizability of our estimates.[30] We address this by using the same sample across both estimation strategies (i.e., restricting to students with at least one pre-treatment observation).

Second, as described above, these two approaches have different bias channels. The FE model is vulnerable to downward bias from declining pre-trends (Ashenfelter-type dynamics), time-varying unobservables that are correlated with application decisions, and time-varying unobservables that are correlated with approval. The applicant design mitigates the first two channels, but it suffers from bias if unobserved "advantage" or disability "severity" predicts both approval and outcomes. To combat this bias, we include rich controls, including documentation and K-12 disability histories, contrasting current-semester approvals with next-semester approvals that are likely delayed for administrative reasons, and conducting formal omitted variable bias sensitivity tests (see Sec-

[29]Full results from this balance regression are available in Figure A5.

[30]Figure A12 shows that students who are approved in their first semester of college are more likely to have learning disabilities, chronic health conditions, and physical disabilities, while students approved in other semesters are more likely to be approved for mental health conditions.

tion 7.5.3).

7.4 Outcomes

We look at both short-run and long-run outcomes. Short-run outcomes are measured in the semester of first application and include the following: a student's decision to withdraw from the semester (binary indicator), number of course withdrawals, and academic performance (semester GPA and count of A/B/C/D/F grades).

Long-run outcomes are measured 1, 2, or 3 years after the application semester. We use both point-in-time and cumulative measures, depending on the outcome. Our main outcomes are persistence, performance, and major choice. Persistence is a point-in-time indicator for being enrolled or graduated at each horizon (e.g., for the one-year outcome, if a student applied in Fall 2021, we check if the student is enrolled or graduated in Fall 2022). We also assess the cumulative number of credits a student earns, excluding the application semester (e.g., for the one-year outcome, if a student applied in Fall 2021, we sum the total credits earned in Winter 2022, Summer 2022, and Fall 2022).[31]

We measure long-run academic performance using the average semester GPA earned in later terms over the same horizons (or at graduation, if earlier), excluding the application term.

Students' major choice is measured using a point-in-time variable of a student's declared major after one, two, or three years, or at graduation (whichever is shorter). We use 7 mutually exclusive categories: undeclared, STEM, business, social sciences, humanities/art, other, and double major.[32]

A practical challenge is censoring. Students apply in different terms and our panel ends in Winter 2025, so not all applicants are observable at each horizon—either because they graduate or the panel ends. This risks conflating compositional changes with treatment effects. We address this in two ways. First, we include college entry cohort by semester of application fixed effects so comparisons are among students with similar time-in-college exposure. Second, we re-estimate effects within balanced windows, restricting to students observable for one, two, or three years to verify that the results are not driven by changing sample composition.

[31] The typical class is 3-4 credits.

[32] Students who are STEM and majoring in another subject are coded as STEM.

7.5 Short-Run: Academic Outcomes

In Table 3, we present results of the impact of accommodations approval on students' short-run—the semester of their application/approval—academic outcomes: decision to withdraw from the semester, number of course withdrawals, and academic performance (number of As, Bs, Cs, Ds, and Fs). We use the Accommodate sample (Fall 2021-Winter 2025) with at least one pre-treatment observation to have a consistent sample across both of our estimation approaches.

Accommodations approval shields students against extreme, negative outcomes. Our FE estimates (panel A) imply that after approval, students are 3pp, or 62%, less likely to completely withdraw from the semester and they withdraw from 0.06 (24%) fewer courses. Their GPA rises slightly, by 0.06 points (2%), relative to their pre-treatment performance.[33] The large effects on extreme outcomes like withdrawals and small effects on grades likely reflects compositional changes (grades are only observed for the students who remain enrolled, who are likely lower performing). The size of our GPA effects are similar in magnitude to Blasey et al. (2023), who also used a student FE model to estimate effects on GPA.[34]

While powerful, a student FE model, as we described above faces two main drawbacks: (1) we will underestimate the impact of accommodations if students are on a downward trajectory prior to seeking accommodations and (2) we cannot estimate effects for students applying for accommodations in their first semester, approximately 40% of all accommodated students. In Figure 6, we present event study plots of the effect of accommodations approval on current semester GPA. Panel A confirms that students are likely to request and be approved for accommodations during a downward spiral.[35] If we adjust for the downward trend (see Figure 7) and assume students' downward trajectory would have continued in the absence of being approved, then the

[33] Observation numbers differ across columns for several reasons. In column 1, we observe students enrolled for the semester. In column 2, we observe students from column 1 who registered for at least one class. In columns 3-8, we observe students from column 2 but drop students where we do not observe class grades (pass/fail courses, incomplete grades, etc.)

[34] The setting for Blasey et al. (2023) differs from ours in several ways. First, they limit their sample to 3 or more semesters of usage (this restriction would cut an additional 20% of our sample). Second, their main independent variable of interest is cumulative semesters of usage, so they are estimating the effect of an additional semester of usage rather than approval. Finally, in their setting students must print out letters and present them to instructors to use accommodations, whereas in our setting students request them in an online system. Approval in our setting is likely more tightly linked to actual usage.

[35] Panel B uses a balanced panel (at least 3 pre/post periods) to confirm this is not driven by compositional changes. Essentially, we present estimates from students applying during their fourth semester of college who we observe in their 7th semester.

estimates imply that in the semester of approval students perform about 0.1 points better—almost double the student FE estimate.[36]

To mitigate the negative bias arising from students' decision to apply, we assess students *after* their application decision, comparing approved students to students that were not approved in panel B. We find larger effects here—approved students are 4.2pp (71%) less likely to withdraw from the semester and withdraw from 0.2 (41%) fewer courses. They also earn a GPA that is 0.09 points higher; this estimate is nearly identical to the estimate we obtain after adjusting for students' pre-treatment trends, indicating robustness to the choice of specification. This alignment between controlling for observables and using fixed effects also suggests that the rich set of observables we use captures most time-invariant differences across students, lending credibility to the cross-sectional comparisons. In panel C, we repeat this exercise including students who applied in their first semester and find qualitatively similar results. This indicates that the main findings are not sensitive to application timing and appear robust despite differences in the composition of disabilities between first-semester and later applicants. For the remainder of the analyses, we use the applicant design and include the full sample of applicants to maximize precision.

7.5.1 Mechanisms

Our framework predicts larger gains where extraneous cognitive load (ECL) is highest (e.g., exam-heavy STEM) and potential spillovers on non-accommodated courses if freed bandwidth lifts performance in other classes taken the same term. We test both ideas here.

Are accommodations gains concentrated where ECL is highest? We assess whether the gains of accommodations are greater in high ECL courses by estimating effects separately by students' entry college—Engineering, Arts & Sciences, Business, and Other[37]—and exploring course-level heterogeneity. In Table 4, we show, consistent with higher ECL, engineering students see larger gains. Approved engineering applicants are about 80% less likely to withdraw from the semester versus 47% in Arts & Sciences, and their semester GPA rises by 0.24 points (8%) versus

[36] To construct the detrended event study estimates, we (i) average pre-treatment point estimates and (ii) subtract all time period estimates by this pre-treatment mean. Confidence intervals are constructed via bootstrapping.

[37] Arts & Sciences includes humanities, social sciences, and natural sciences; Engineering includes all engineering majors; Business is the undergraduate business program; Other includes Nursing, Music/Theater/Dance, Art & Design, Information, Kinesiology, Public Health, and Architecture.

0.06 points (2%).

The above exercise shows students who are likely to take higher ECL courses disproportionately benefit from accommodations; however, it is limited because we do not observe performance in specific courses. To more precisely assess this question about ECL, we turn to our student x semester x course data. We run the following regression:

$$\begin{aligned} Y_{ic} =& \alpha + \beta Accommodations_i + X_i + Cohort_i \times Semester_t + ShareAccommodated_{ic} \\ &+ Course_c + \epsilon_{ic} \end{aligned} \tag{3}$$

Here, Y_{ic} is the outcome for student i in course c (course withdrawal or course grade) in the semester of application. Course withdrawal is a binary indicator and course grade is on a 0-4 scale based on letter grade (A+/A = 4; A- = 3.7; B+ = 3.4; B = 3; B- = 2.7; C+ = 2.4; C = 2; C-=1.7; D+ = 1.4; D = 1; D- = 0.7; F=0). $Accommodations_i$ is a binary indicator for accommodations approval. We include the same vector for individual-level controls (X_i) as equation 2, add a course fixed effect ($Course_c$) to account for time-invariant course characteristics (e.g., difficulty of material), and control for the leave-one-out share of students approved for accommodations in the course ($ShareAccommodated_{ic}$) to adjust for the possibility that having more students with accommodations affects the grading distribution. We run this regression separately by course type: STEM (non-engineering), engineering, business, social sciences, humanities/art, and other. This regression asks: do students approved for accommodations perform better in similar courses compared to students not approved for accommodations?

We present the results of this regression in Figure 8. In panel A, we show that students who are approved for accommodations are less likely to withdraw from all courses. The effect for students taking engineering courses is larger than for social science and humanities/art courses (45% vs 43% and 29%, respectively). In addition, in panel B, we show the grade-boost is also largest in engineering courses—the average course grade boost in engineering courses is 4.9% vs 2.6% for social science and 3.4% for humanities/art courses. Effects in non-engineering STEM are smaller than engineering, plausibly because engineering courses rely more on timed, proctored assessments and tightly specified workflows (higher ECL), while many life-science courses include labs, projects, or partial credit that diffuse time pressure.

Usage vs. spillovers. In our setting, accommodations are requested at the course level, not the semester level. The marginal cost of requesting for one class is essentially the same as requesting for all, yet approved students request accommodations in only 80% of their classes, on average. We exploit this to separate direct use from within-term spillovers. At the student x semester x course-level, we re-estimate equation 3 in two ways: (i) replacing the treatment with "approved and requested for this course" to identify the direct-use effect and (ii) replacing it with "approved but not requested for this course" to test for spillovers into classes where accommodations are not requested. The first comparison captures the effect where supports are actually used and the second asks whether approval changes performance in non-requested courses taken in the same term.

Figure A6 and A7 indicate that the gains are concentrated in courses where accommodations are actually requested; we do not detect positive spillovers in non-requested courses. Given the endogeneity of requesting (students are more likely to request in harder, test-heavy courses), we interpret this as suggestive evidence of gains from accommodations coming from directly reducing ECL rather than course spillovers.

7.5.2 Heterogeneity

We examine short-run effects by student demographics in Table A7.[38] Patterns suggest modest heterogeneity: after approval, men appear less likely than women to withdraw from the semester (-5pp vs -2pp) and earn higher GPAs; Asian students show larger benefits than their white peers, consistent with a "more marginal applicant" story given their lower application and approval rates. Most subgroup differences are not statistically distinguishable, and, with many outcomes, some contrasts are likely spurious. We view these results as suggestive.

[38]We also probe heterogeneity by disability type by re-estimating effects after sequentially dropping each approved group in Figure A8. The point estimates on withdrawing from the semester and semester GPA attenuate slightly when we drop students with mental health conditions but remain statistically significant. This attenuation is expected for two reasons: (i) if mental-health approvals have larger effects or are more positively selected, removing them reweights the treated group toward categories with smaller effects, mechanically lowering the average; and (ii) because we cannot symmetrically exclude mental health students from the control group (we only observe disability category for approved students), dropping them only on the treated side shrinks the treated–control contrast. Thus, the persistence of statistical significance under this conservative test indicates that category composition is unlikely to drive our main findings.

7.5.3 Sensitivity and Robustness

The primary threat to identifying the causal effect of accommodations is omitted variable bias: unobserved traits may affect both who receives accommodations and how they perform. Although our models control for rich observables—including household income, prior GPA, and standardized test scores—these controls may only imperfectly capture underlying factors such as disability severity, motivation, or family resources. We take two additional steps to assess threats of omitted variable bias. First, we use formal sensitivity analyses to ask how strong unobserved selection would need to be to wipe out our estimates and to produce bias-adjusted effects. Second, we conduct targeted robustness checks to rule out the most plausible forms of bias.

Sensitivity to omitted variable bias. We begin with the approach of Frank et al. (2013) and Xu et al. (2019), which asks a simple but revealing question: how much bias would be required to overturn our main findings? Specifically, we calculate the proportion of observations that would have to be ”replaced” with cases consistent with the null hypothesis (no effect of accommodations) for results to lose statistical significance at the conventional $\alpha = 0.05$ level. The threshold is high: about 3,500-4,000 (65-70%) observations when outcomes are semester withdrawal and GPA.

The above approach speaks to *statistical significance* but does not address the extent to which omitted variables could meaningfully alter *magnitude*. Therefore, we turn to the coefficient stability framework of Altonji et al. (2005) and Oster (2019). This method uses movements in the accommodations coefficient and in R^2 as controls are added to infer how strongly unobservables would have to predict treatment to alter our results. Intuitively, if adding rich observables barely changes the coefficient but sharply increases R^2, it suggests that unobservables are unlikely to drive the result. We present results under two benchmarks with a hypothetical maximum R^2: (i) $R_{\text{max}} = 1.3 \times R_{\text{controlled}}$, Oster's recommended benchmark, and (ii) $R_{\text{max}} = 1$, a deliberately conservative case where unobservables could explain all remaining variation. This conservative scenario assumes no measurement error or idiosyncratic variation. As shown in Oster (2019), only about 40% of RCT estimates would survive this threshold, while nearly all survive the 1.3× benchmark.

Figure A9 plots bias-adjusted coefficients across values of δ, the proportional-selection parameter. For GPA, the bias-adjusted estimate is notably stable: with $\delta = 1$ (unobservables as predictive as observables), the effect falls only slightly—from 0.119 to 0.103—under the 1.3× benchmark.

Under the conservative $R_{\max} = 1$ scenario, the effect declines further and approaches zero, but only under extreme assumptions. In Figure A10, we repeat this exercise with in-state students and additional K-12 observables that are likely correlated with both accommodations approval and academic outcomes: prior documented disabilities (ever having an IEP or 504 plan in HS), standardized test scores (grades 8 and 11), attendance, disciplinary records (suspensions and expulsions), measures of economic disadvantage, and high school characteristics (demographics, average test scores, and urbanicity). Including these variables significantly increases the R^2—by 50%—but barely moves the treatment effect coefficient, suggesting that observables are capturing much of approval selection and there is limited scope for unobservables to overturn these results. We see similar patterns but wider intervals when the outcome is semester withdrawals, reflecting the lower explanatory power of observed covariates for this rare outcome.

Together, these sensitivity analyses indicate that our main findings are robust to moderate omitted variable bias. The approach of Xu et al. (2019) shows that bias would need to be implausibly large to erase significance, while Oster (2019) demonstrates that bias of realistic magnitudes would not meaningfully alter the size or sign of the estimates.

Additional robustness tests. We show results from targeted robustness checks to rule out plausible forms of bias in Table 5. In panel A, we focus on students who apply in the same semester and compare those that are approved in the semester of application to those who are approved in the very next semester. Delays in approval often arise because students apply late in the term, when intake appointments and evaluations are backlogged, or because they are still assembling required documentation.[39] This comparison is valuable because it narrows the set of unobservables like disability severity: students are observed applying at the same time, and differences in outcomes primarily reflect the approval decision. Figure A11 shows that, aside from slightly higher prior achievement for immediately approved students, the two groups are otherwise observably similar—a difference we further adjust for by controlling for prior achievement in the regression. To address residual differences in application timing, we include week-of-semester fixed effects, which—while imperfect—capture many of the factors correlated with late application (e.g., time management).

[39] Among roughly 5,600 first-time applicants, about 4,000 are approved during their application semester, while 350 are approved in a later term—three-quarters of them the very next semester. Figure A13 shows students who are approved in a future term apply disproportionately later in the semester relative to those approved immediately.

Relative to our baseline estimates, the point estimates in this "future-approval" comparison are slightly larger: the withdrawal rate falls by 0.053 versus 0.031 in the baseline, course withdrawals by 0.277 versus 0.163, and GPA gains are larger at around 0.190 versus 0.120. That these effects are relatively comparable—even when restricting the comparison to applicants within the same semester and controlling for week-of-application—suggests that unobserved selection into approval timing is unlikely to explain our main results. If anything, baseline estimates are conservative.

In panel B, we examine the role of documentation. This is a key proxy for advantage: students with greater resources are more likely to obtain medical documentation at intake. Submitting documentation reflects both the ability to navigate administrative barriers and access to external evaluations, and is strongly predictive of approval: 52% of approved students submit documentation at intake compared to 25% of those denied. We find that controlling for submitting documentation at intake status does not meaningfully change the estimates.

In panels C-E, we subset our sample to instate students to take advantage of the fact that we have unusually rich K-12 covariates that proxy for disability, preparedness, and family resources. Students' prior disability status may bias our results downward if the most severely disabled students had a documented disability in K-12, and although students with IEPs/504 plans make up a small share of the overall in-state student body (less than 5%), they make up a sizable share of in-state applicants (14%). In panel D, we control for whether a student had an IEP or 504 plan, and find that our estimates remain unchanged (see panel C for results without those controls). Adding the full set of K-12 controls (Panel E)—prior test scores, disciplinary incidents, attendance, and school characteristics—leaves estimates virtually unchanged, further indicating that bias from unobserved variables is limited.

Another concern in our applicants design is that the control group (unapproved students) may be affected by treatment (a SUTVA violation). The treatment effect will be biased upwards if unapproved students perform worse in a class if they are exposed to more accommodated peers (if grades are curved or zero-sum). It may be biased downwards if more accommodated peers improve outcomes for everyone through more accessible material or pacing. We address this issue in two ways using student x semester x course-level data. First, we estimate effects on course grades while controlling for the leave-one-out class-share of accommodated peers. Second, we interact approval with the share of accommodated peers.

In Table A6, we present results from this investigation. In panel A, we present results without peer controls. Compared to unapproved applicants, approved students are 71% less likely to withdraw from their course and earn a 3% higher course grade, primarily due to approved students receiving more As and fewer Bs and Cs. When we adjust for peers with accommodations in panel B, the point estimates are unchanged. When we include an interaction term, it is insignificant across all outcomes. This exercise suggests there is minimal evidence of spillovers.

Together, these tests paint a consistent picture. Formal sensitivity analyses show that implausibly large bias would be required to erase significance or reverse the sign of effects. Targeted checks suggest that omitted variable bias is unlikely to meaningfully distort results: controlling for prior disability, documentation, and K-12 characteristics barely shifts estimates, and timing-based comparisons yield similar effects. We also see limited evidence of spillover effects (SUTVA violation). While no observational design can fully rule out omitted variable bias, the convergence of multiple approaches increases confidence that estimated benefits of accommodations are genuine.

7.6 Long-Run Outcomes

We now follow applicants beyond the approval term and examine long-term outcomes: persistence, performance, and major choice. These analyses will also rely on our comparison of approvals to non-approvals (equation 2) and use our full sample of first-time applicants from the Accommodate data, including first-semester applicants (panel C of Table 3).

7.6.1 Persistence

We show that students approved for accommodations are more likely to persist in college in Table 6. Column 1 shows a 5pp (5%) increase in the probability a student is enrolled or has graduated one year later among students observable for at least one year (applications from Fall 2021–Winter 2024). One-year effects are not driven by compositional change as they are similar in size when we restrict our sample to students observable for two years (column 2) and three years (column 4). Not surprisingly, one-year effects are primarily driven by the enrollment margin rather than the graduation margin (the one-year effect on the probability of graduation is zero).

Columns 3 and 5 show that two years later, students approved for accommodations are 3-5pp more likely to be enrolled or graduated. When separating by the enrollment and graduation margins, we find that enrollment effects dissipate at the two-year mark, falling to a noisy 0-3pp increase. This apparent attenuation around the two-year mark partly reflects the competing graduation margin. Approved students are more likely to have graduated by then, with graduation rates 3–4pp (10%) higher two years after application (though, not statistically significant at conventional levels). In other words, the "enrolled" effect falls as some of the treatment effect shows up as earlier completion.

We also find students earn more credits over the course of their college career after accommodations approval (i.e., take and complete more classes after the application semester). Excluding the application semester by construction, approved students accumulate about 1.4–1.8 more credits (8%) over the first year relative to non-approved applicants, and 1.8–3.2 more credits (5–10%) over two years (columns 3 and 5). Because these measures are cumulative and omit the application term, the gains are not simply a mechanical result from fewer withdrawals during the application semester; they reflect sustained persistence after approval.

7.6.2 Academic performance

Students approved for accommodations continue to post stronger grades beyond the approval term. In column 1 of panel A in Table 7, we find students' average semester GPA over the next year is 0.10 points (3%) higher among students observable for at least one year (applications from Fall 2021–Winter 2024). These gains are not driven by the application term because it is excluded by construction. One-year effects are slightly smaller for students observable for at least two years (column 2) and three years (column 4). Point estimates and precision fall for average semester GPA measured two and three years post-application.

This attenuation could reflect several mechanisms. It could reflect true fade-out, as is common in the early childhood education literature (Elango et al., 2015). Another equally plausible channel is sorting into more demanding coursework—especially in STEM—where grades compress even as students persist and accumulate credits. Similarly, compositional changes could produce this pattern of fade-out if low-performing students are more likely to remain enrolled.[40]

[40] Inconsistent use of accommodations could also matter, but our setting allows us to more cleanly assess the role of persistence and course choice. We find, for example, that conditional on approval, students request accommodations more often in harder courses (lower average course GPA). This is an endogenous choice that will mechanically create a negative relationship between accommodations use and GPA.

We test for the role of persistence in Figure A14, where we re-estimate our long-term regression on enrollment separately by high-achieving and low-achieving students as measured by their cumulative GPA in the semester prior to accommodations application (excluding first-semester applicants). Approval boosts persistence for lower-GPA students—about 9pp after one year—while effects for higher-GPA students are near zero. Impacts fade for both groups by years 2–3. This implies increased retention of low-performing students mechanically results in a composition shift that dampens average GPA in the long-term, at least for one year.

Course choice tells a complementary story. We find evidence that after approval, students take more difficult courses.[41] To show this, we rerun our long-run analysis where we replace the GPA outcome with a course-bundle GPA in a semester (we average the grades in a class on 0-4 scale, excluding the focal student, and then aggregate this measure to the student x semester level). A lower bundle GPA implies tougher coursework. Figure A15 shows students take harder courses after accommodations approval. The effects are concentrated in our largest college (the college of arts & sciences)—students take classes with a 0.05 lower GPA bundle one year after application and a 0.09 lower GPA bundle 3 years after application. Results for other colleges are noisier, but are suggestive of either a null or negative effect on course-bundle GPA (taking more difficult courses).

The findings here suggest that much of the GPA fadeout reflects who stays enrolled (more lower-GPA students) and where approved students go academically (persisting in or sorting into "harder" courses), not the disappearance of short-run academic gains.

7.6.3 Major choice

In panel B of Table 7, we show that when students are approved for accommodations, STEM declaration increases. One year after application, STEM declaration increases by 12% for approved students, and coincides with an 8% decline in humanities/arts. Effects on STEM majoring are larger when we restrict to cohorts observable for two and three years (15-22%), suggesting they are not driven by compositional change. Unlike GPA, these effects do not disappear over time. Two years after applying for accommodations, approved students are still 12-16% more likely to declare a STEM major than unapproved students. Because women disproportionately use accommodations,

[41] Below, we show engineering students are more likely to persist in STEM majors. STEM courses have, on average, lower grades than non-STEM courses—75% of non-STEM courses are As but only 65% of STEM course grades are As—which further pull down long-run GPA gains.

a useful benchmark is the female–male STEM major gap at our university (18pp). The estimated STEM effects imply a 29% gap closure after three years, or over 100 additional women in STEM.

Given these STEM findings, a natural question is : how do accommodations increase STEM major declarations? As described in our conceptual framework, there are two margins through which accommodations approvals can raise STEM rates: persistence and upgrading/re-optimization. On the persistence margin, approvals reduce exits from STEM—students are less likely to withdraw, fail, or switch after poor performances in STEM courses. On the upgrading margin, approvals may increase expected STEM grades relative to non-STEM because STEM courses rely heavily on tests compared to other majors.

We test for these two pathways in Table A8, where we measure the effect of accommodations one, two, and three years later separately by the engineering college and the largest college (arts & sciences). We find evidence that the effects we observe are driven by persistence. Almost all of the effect on STEM selection is driven by students who began at the engineering college—among students who began in the engineering college, approved applicants are 9-16pp more likely to declare STEM (and 9-16pp less likely to remain undeclared) after one year. The STEM effects persists two years later but the margin narrows and precision falls, partly reflecting a drop in sample size. The estimates on STEM major are positive for students in the college of arts & sciences, but are not statistically significant at conventional levels.

7.6.4 Heterogeneity

We examine one-year effects by student demographics in Table A9.[42] We focus on the one-year horizon because subgroup cells thin quickly. Patterns suggest modest heterogeneity: men appear more likely than women to be enrolled one year later (8pp vs. 3pp), while women are more likely to declare STEM; middle-income students show larger GPA gains than low- or high-income peers, consistent with a "more marginal applicant" story given their lower application and approval rates. Most subgroup differences are not statistically distinguishable, and, with many outcomes, some contrasts are likely spurious. We view these results as suggestive.

[42]We also probe heterogeneity by disability type by re-estimating effects after sequentially dropping each approved group in Figure A16. Enrollment effects attenuate when we drop students with learning disabilities, and STEM declaration effects attenuate when we drop students approved for mental-health conditions—suggesting these groups disproportionately drive the respective gains. Because disability type is only observed for approved students, these patterns are descriptive and should be interpreted cautiously.

8 Discussion

In this paper, we study academic accommodations at a large public flagship. We track a decade of trends, document who uses supports, and estimate effects on performance, persistence, and major choice. Three facts stand out. First, usage rose sharply—from 4% to 10% between 2011 and 2024. Second, there exist large gaps in usage across race, gender, and SES. Third, approvals matter. Using student fixed effects and comparisons of approved and non-approved applicants with rich controls, we find accommodations usage is associated with fewer withdrawals, higher GPAs, and greater persistence–especially in STEM. The STEM effect reflects persistence among existing STEM students (engineering in particular), not sorting into STEM. These results clarify drivers of growth and gaps in use, inform debates about accommodations in higher education, and speak to strengthening and diversifying the STEM pipeline.

Lower application rates explain most of the gender and Asian–white gaps, consistent with stigma and help-seeking norms (Angrist et al., 2009; Jacob, 2002; Sen, 2004). Among applicants, higher-income students clear approval at higher rates, consistent with better documentation and faster follow-up (Weis & Bittner, 2022). These facts point to concrete steps: normalize early disclosure in first-year touchpoints, use targeted outreach to combat possible stigma, and expand low- or no-cost psychological evaluations.

What do the effects mean for longer-run choices? We find that approvals both lift near-term performance and shift course portfolios towards STEM by improving persistence through gateway requirements. That margin matters for equity: persistence in STEM is linked to higher earnings (Kang et al., 2018). Whether these gains translate into completed STEM degrees and labor-market returns remains an open question; our results suggest this is a promising channel to test, especially given the concentration of effects in engineering.

Accommodations use has surged over the past decade and is likely to keep rising. Understanding how they are used, how they work, and whom they help is more urgent than ever. This study opens a practical research agenda and sparks new and pressing questions. Do peers' accommodations help or hurt classmates, and when? Grading policies, assessment mix, and course difficulty could shape spillovers. How do students use accommodations—do they strategically employ them in more difficult courses? Which components—extended time, reduced-distraction rooms, assistive tech—

drive the gains we measure, especially for students with mental-health–related constraints? And do short-run academic improvements translate into on-time graduation, STEM entry, and earnings? The linked data infrastructure used here—course-by-course requests, approval timing, and rich outcomes—makes these questions feasible to answer in future work.

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Tables

Table 1. Disability and Accommodations at University

	Overall sample	Ever used accommodations
Panel A. Disability (%)		
Learning disability (e.g., ADHD, intellectual disabilities)	5.74	50.31
Mental health (e.g., anxiety, depression, OCD)	5.69	48.23
Autism spectrum disorder	0.36	2.92
Chronic health conditions (e.g., diabetes, epilepsy)	1.96	16.39
Physical disability (e.g., mobility, hearing, vision, deaf)	0.78	5.44
Other disabilities (e.g., speech)	1.61	9.09
Missing disability	1.62	1.40
Approved accommodations (%)		
Testing (e.g., extended time, separate location)	10.09	93.32
Assignment (e.g., extra time, advanced access/detail)	1.98	18.04
Accessibility and mobility (e.g., wheelchair, preferential seating)	0.52	4.70
Accessible formats (e.g., larger font, braille materials)	1.03	9.50
Assistive technology/support service (e.g., screen reader, voice-to-text)	3.62	33.37
Attendance flexibility (e.g., additional absences)	1.92	17.05
Other accommodations	0.36	0.53
N	62133	6359

Notes: This table displays the types of disabilities and accommodations reported in the Accommodate system for students enrolled in Fall 2021-Winter 2025. Note that disability and accommodations types are only reported for students approved for accommodations.

Table 2. Predicting Accommodations Usage by Out-of-State and In-State Status

	(1)	(2)	(3)	(4)	(5)	(6)
	Ever Accommodations (0/1)					
	Out-of-state	In-state				
Female	0.042***	0.058***	0.059***	0.010***	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Asian	-0.066***	-0.045***	-0.035***	-0.005*	-0.005*	-0.005*
	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
Black	-0.049***	-0.015*	-0.005	-0.004	-0.005	-0.005
	(0.009)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)
Hispanic	-0.007	0.009	0.011	0.007	0.004	0.004
	(0.006)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)
Other	-0.040***	0.011*	0.014**	0.005	0.004	0.004
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
First-gen	-0.021***	-0.015***	-0.010**	-0.007**	-0.006**	-0.006**
	(0.006)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
HH income $50-100k	-0.025***	-0.027***	-0.026***	-0.002	-0.001	-0.001
	(0.007)	(0.006)	(0.006)	(0.004)	(0.003)	(0.003)
HH income $100-200k	-0.023***	-0.028***	-0.030***	0.001	0.001	0.001
	(0.007)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
HH income $200k+	-0.001	-0.013**	-0.015**	0.007**	0.008**	0.007**
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
HH income missing	-0.004	-0.018***	-0.019***	0.009**	0.009**	0.009**
	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)
HS GPA	-0.083***	-0.127***	-0.099***	0.012	0.013	0.011
	(0.013)	(0.017)	(0.016)	(0.010)	(0.009)	(0.009)
SAT (std)	0.017***	0.006***	0.005***	0.003***	0.003***	0.003***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Total APs	-0.006***	-0.004***	-0.004***	-0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
International	-0.062***					
	(0.006)					
IEP/504 plan in HS			0.422***	0.108***	0.105***	0.100***
			(0.010)	(0.006)	(0.006)	(0.006)
Applied				0.694***	0.583***	0.594***
				(0.003)	(0.004)	(0.003)
Documentation submitted					0.274***	
					(0.005)	
Doc from ext med provider						0.235***
						(0.005)
Doc from uni provider						0.070***
						(0.020)
K-12 doc						0.174***
						(0.015)
Other doc (FERPA, picture, etc.)						0.244***
						(0.010)
N	31481	30352	30352	30352	30352	30352
R-squared	0.050	0.035	0.091	0.673	0.701	0.699
Outcome mean	0.103	0.101	0.101	0.101	0.101	0.101

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table present results from a linear probability model, where the outcome is a binary indicator that is equal to 1 if a student ever used accommodations and 0 otherwise. All regressions include starting semester fixed effects. The sample includes students enrolled from Fall 2021-Winter 2025. Column 1 consists of out-of-state students (including international) and columns 2-5 consist of only in-state students. Applied is an indicator for requesting a meeting with the disability office. Documentation submited is an indicator for whether a student submitted a documentation during their initial meeting request. Documentation from external providers include primary care physicians, specialists, and mental health professions. Documentation from university providers include university counseling services or health services. K-12 documentation includes IEPs and 504 plans and other documentation include student self-reports.

Table 3. Short-Run Impact of Academic Accommodations

	(1) Withdrawal semester (0/1)	(2) Number of course withdrawals	(3) Semester GPA	(4) #As	(5) #Bs	(6) #Cs	(7) #Ds	(8) #Fs
Panel A. Student FE								
Approved	-0.026***	-0.058***	0.062***	0.099***	-0.014	0.002	-0.008	-0.018**
SE	(0.006)	(0.020)	(0.014)	(0.036)	(0.027)	(0.016)	(0.007)	(0.007)
N	17857	17010	16347	16347	16347	16347	16347	16347
Outcome mean	0.042	0.242	3.419	2.561	0.939	0.280	0.051	0.045
Panel B. Comparison of approved vs not approved (at least 1 pre-treatment period)								
Approved	-0.042***	-0.199***	0.091***	0.169***	-0.006	0.002	-0.011	-0.027**
SE	(0.007)	(0.032)	(0.024)	(0.057)	(0.041)	(0.026)	(0.011)	(0.012)
N	3537	3482	3380	3380	3380	3380	3380	3380
Control mean	0.059	0.462	3.226	2.302	1.075	0.378	0.082	0.058
Panel C. Comparison of approved vs not approved								
Approved	-0.031***	-0.163***	0.120***	0.223***	-0.046	-0.018	-0.014	-0.036***
SE	(0.005)	(0.024)	(0.021)	(0.049)	(0.034)	(0.020)	(0.009)	(0.010)
N	5629	5569	5444	5444	5444	5444	5444	5444
Control mean	0.050	0.305	3.334	2.383	0.975	0.313	0.063	0.048

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. This table uses student x semester data from Fall 2021-Winter 2025 to estimate the impact of accommodations on student short-run academic outcomes (semester of application) among applicants. Column 1: term withdrawal (binary, observed only for students who initially enroll that term). Column 2: number of course withdrawals (observed only for students enrolled in at least one course). Columns 3–8: grade outcomes (observed only for graded, non–pass/fail courses). Panel A is a student fixed effect model, where we include student and semester x cohort FEs (see equation 1). Panel B and C compares students who are approved for accommodations to students that are not approved (see equation 2, where controls include college entry cohort x semester of application FE and the following controls: gender, race, gender, race, household income, high school GPA, SAT scores, number of AP classes, lagged cumulative GPA, lagged indicators for athlete status and major declared, major type, home college (Arts & Sciences, Business, Engineering), an indicator for applying in a non-enrolled semester. Panels A–B exclude first-semester applicants; panel C includes those applying in their first semester. For this analysis, we impute pre-accommodations variables with zeroes and include missing indicator for first semester of attendance. We use robust standard errors.

Table 4. Short-Run Impact of Academic Accommodations by College

	(1) Withdrawal semester (0/1)	(2) Number of course withdrawals	(3) Semester GPA	(4) #As	(5) #Bs	(6) #Cs	(7) #Ds	(8) #Fs
Panel A. College of engineering								
Approved	-0.070***	-0.295***	0.238***	0.344**	-0.046	0.046	-0.087**	-0.101**
SE	(0.020)	(0.097)	(0.075)	(0.154)	(0.113)	(0.077)	(0.034)	(0.040)
N	646	637	619	619	619	619	619	619
Control mean	0.087	0.645	2.966	1.941	1.183	0.464	0.144	0.138
Panel B. College of arts and sciences								
Approved	-0.021***	-0.162***	0.063**	0.102	0.052	0.003	0.005	-0.010
SE	(0.006)	(0.034)	(0.027)	(0.065)	(0.044)	(0.027)	(0.012)	(0.013)
N	2951	2926	2860	2860	2860	2860	2860	2860
Control mean	0.044	0.440	3.282	2.306	0.965	0.330	0.067	0.068
Panel C. College of business								
Approved	-0.023	-0.055	0.160**	0.289	-0.562*	-0.071		0.005
SE	(0.019)	(0.099)	(0.081)	(0.351)	(0.313)	(0.075)		(0.009)
N	263	257	256	256	256	256	256	256
Control mean	0.016	0.169	3.396	2.525	2.153	0.203	0.000	0.000
Panel C. College other								
Approved	-0.022***	-0.099***	0.130***	0.248***	-0.079	-0.060*	-0.010	-0.060***
SE	(0.007)	(0.036)	(0.038)	(0.096)	(0.062)	(0.036)	(0.016)	(0.020)
N	1769	1749	1709	1709	1709	1709	1709	1709
Control mean	0.062	0.404	3.223	2.429	1.059	0.388	0.092	0.099

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table uses student x semester data from Fall 2021-Winter 2025 to estimate the impact of accommodations on student short-run academic outcomes (semester of application) by the initial college a student was enrolled in. Column 1: term withdrawal (binary, observed only for students who initially enroll that term). Column 2: number of course withdrawals (observed only for students enrolled in at least one course). Columns 3–8: grade outcomes (observed only for graded, non–pass/fail courses). The college of arts and sciences includes students studying the humanities, social sciences, and natural sciences; engineering includes all engineering majors; business is the undergraduate business program; other covers undergraduate programs outside these three (e.g., nursing; music, theater, and dance; art and design; information; kinesiology; public health; architecture). We compare students who are approved for accommodations to students that are not approved (see equation 2, where controls include cohort x semester FE and the following controls: gender, race, gender, race, household income, high school GPA, SAT scores, number of AP classes, lagged cumulative GPA, lagged indicators for athlete status and major declared, major type, and an indicator for applying in a non-enrolled semester. The sample includes all first-time applicants. For this analysis, we impute pre-accommodations variables with zeroes and include missing indicator for first semester of attendance. We use robust standard errors.

Table 5. Short-Run Impact of Academic Accommodations Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Withdrawal semester (0/1)	Number of course withdrawals	Semester GPA	#As	#Bs	#Cs	#Ds	#Fs
Panel A. Comparing to students who receive accommodations next semester								
Approved	-0.053***	-0.277***	0.190***	0.380***	-0.104	-0.060	-0.031	-0.026
SE	(0.014)	(0.065)	(0.046)	(0.097)	(0.070)	(0.048)	(0.023)	(0.025)
N	4351	4323	4253	4253	4253	4253	4253	4253
Control mean	0.079	0.549	3.192	2.088	1.121	0.388	0.092	0.067
Panel B. Control for submitting documentation								
Approved	-0.032***	-0.177***	0.124***	0.234***	-0.045	-0.021	-0.014	-0.035***
SE	(0.005)	(0.025)	(0.021)	(0.050)	(0.035)	(0.021)	(0.009)	(0.010)
N	5629	5569	5444	5444	5444	5444	5444	5444
Control mean	0.050	0.305	3.334	2.383	0.975	0.313	0.063	0.048
Panel C. In-state sample								
Approved	-0.033***	-0.181***	0.128***	0.208***	-0.016	0.016	-0.007	-0.049***
SE	(0.008)	(0.044)	(0.034)	(0.078)	(0.055)	(0.037)	(0.015)	(0.016)
N	2165	2145	2081	2081	2081	2081	2081	2081
Control mean	0.057	0.507	3.171	2.125	1.060	0.381	0.087	0.052
Panel D. In-state sample, controlling for IEP/504 plan								
Approved	-0.033***	-0.183***	0.128***	0.214***	-0.020	0.017	-0.006	-0.049***
SE	(0.009)	(0.044)	(0.034)	(0.078)	(0.055)	(0.037)	(0.015)	(0.016)
N	2165	2145	2081	2081	2081	2081	2081	2081
Control mean	0.057	0.507	3.171	2.125	1.060	0.381	0.087	0.052
Panel E. Full set of K-12 controls for in-state students								
Approved	-0.034***	-0.186***	0.141***	0.230***	-0.008	0.004	-0.010	-0.051***
SE	(0.008)	(0.044)	(0.035)	(0.078)	(0.055)	(0.037)	(0.015)	(0.016)
N	2165	2145	2081	2081	2081	2081	2081	
Control mean	0.057	0.507	3.171	2.125	1.060	0.381	0.087	0.052

*Notes:** p<0.1, ** p<0.05, *** p<0.01. This table uses student x semester data from Fall 2021-Winter 2025 to estimate the impact of accommodations on student short-run academic outcomes (semester of application) among applicants. Column 1: term withdrawal (binary, observed only for students who initially enroll that term). Column 2: number of course withdrawals (observed only for students enrolled in at least one course). Columns 3–8: grade outcomes (observed only for graded, non–pass/fail courses). We compare students who are approved for accommodations to students that are not approved (see equation 2, where controls include cohort x semester FE and the following: gender, race, gender, race, household income, high school GPA, SAT scores, number of AP classes, lagged cumulative GPA, lagged indicators for athlete status and major declared, major type, home college (Arts & Sciences, Business, Engineering), and an indicator for applying in a non-enrolled semester. Panel A compares students approved in the application semester to those approved in the subsequent semester while controlling for week of semester of application FE (outcomes are still measured in the semester of application). Panel B controls for whether a student submitted documentation when filing their intake form. Panels C-E subset to in-state students. The full set of controls in panel E include student-level variables—such as prior documented disabilities (ever having an IEP or 504 plan in HS), standardized test scores (grades 8 and 11), attendance, disciplinary records (suspensions and expulsions), and measures of economic disadvantage—and high school characteristics—demographics, average test scores, and urbanicity. We impute pre-accommodations variables with zeroes and include missing indicator for first semester of attendance. We use robust standard errors.

Table 6. Long-Run Impact of Academic Accommodations on Persistence

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Observable in data for at least...					
	1 year	2 years		3 years		
Outcome measured:	One year	One year	Two year	One year	Two year	Three year
Enrolled in semester or graduated	0.047***	0.052***	0.057***	0.038*	0.032	0.057**
	(0.010)	(0.012)	(0.016)	(0.019)	(0.021)	(0.028)
	[0.863]	[0.876]	[0.812]	[0.848]	[0.838]	[0.755]
Enrolled in semester	0.048***	0.050***	0.027	0.029	-0.005	0.025
	(0.013)	(0.016)	(0.019)	(0.025)	(0.030)	(0.030)
	[0.738]	[0.723]	[0.512]	[0.711]	[0.477]	[0.321]
Graduated	-0.001	0.002	0.030*	0.009	0.037	0.032
	(0.010)	(0.014)	(0.017)	(0.022)	(0.030)	(0.030)
	[0.124]	[0.148]	[0.300]	[0.137]	[0.361]	[0.433]
Cum. credits earned	1.464***	1.834***	3.152***	1.423*	1.810	3.253*
	(0.364)	(0.470)	(0.801)	(0.753)	(1.299)	(1.709)
	[18.849]	[22.861]	[31.633]	[21.478]	[35.960]	[36.435]
N	4150	2545	2545	1124	1124	1124

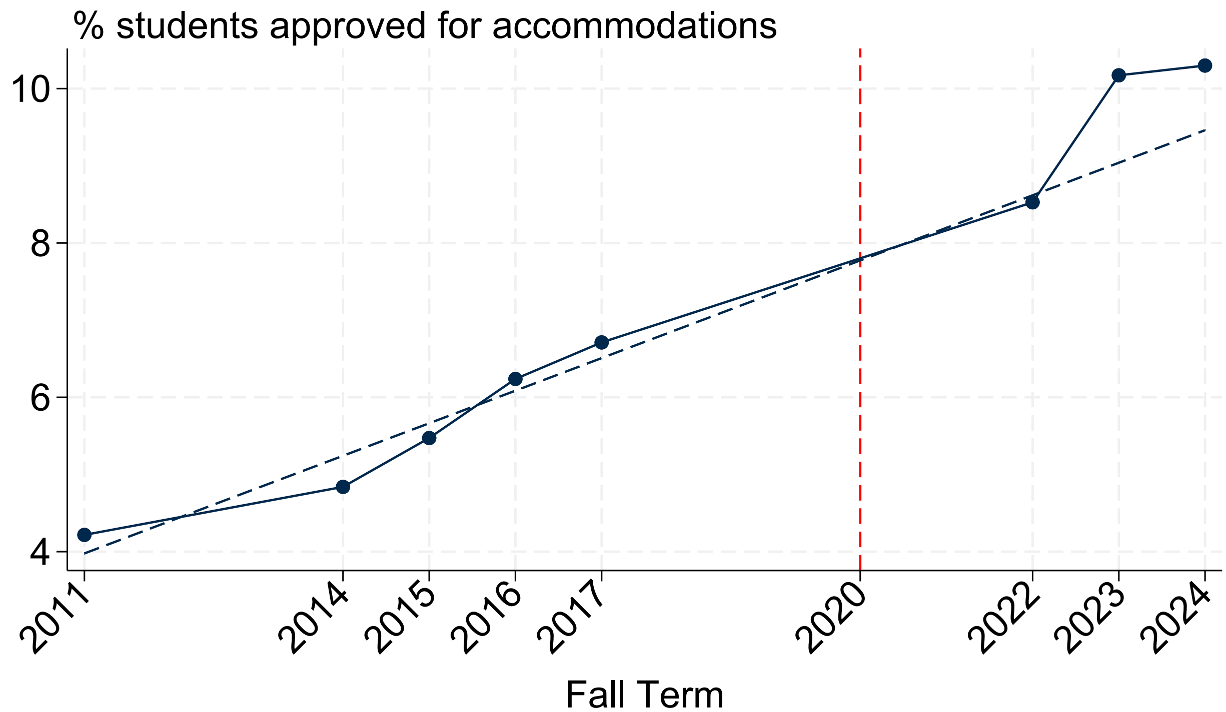
Notes: * p<0.1, ** p<0.05, *** p<0.01. This table uses student x semester data from Fall 2021-Winter 2025 to estimate the impact of accommodations on student long-run academic outcomes (from semester of application). See equation 2 for details. Enrolled and graduation are binary indicators that are equal to one if the student was observed or had a graduation date one, two, or three years later (e.g., for a student applying in Fall 2021 they are enrolled in Fall 2022 or graduated that semester or before then). Cumulative credits earned is the total number of credits earned between application and one, two, and three years later or up until graduation (whichever is shorter). We do not include the semester of application observation when creating this outcome. The sample in column 1 includes students applying in Fall 2021-Winter 2024, the sample in columns 2-3 includes students applying in Fall 2021-Winter 2023, and the sample in columns 4-6 includes students applying in Fall 2021-Winter 2022. Controls include cohort x semester FE and the following controls: gender, race, gender, race, household income, high school GPA, SAT scores, number of AP classes, lagged cumulative GPA, lagged indicators for athlete status and major declared, major type, home college (Arts & Sciences, Business, Engineering), and an indicator for applying in a non-enrolled semester. We impute pre-accommodations variables with zeroes and include an indicator for first semester. We use robust standard errors. Control means are in brackets.

Table 7. Long-Run Impact of Academic Accommodations on GPA and Major Choice

	(1)	(2)	(3)	(4)	(5)	(6)
		Graduated or observed in data for at least...				
	1 year	2 years		3 years		
Outcome measured:	One year	One year	Two year	One year	Two year	Three year
Panel A. Academic performance						
Semester GPAs (avg)	0.095***	0.066**	0.063**	0.043	0.031	0.022
	(0.023)	(0.027)	(0.026)	(0.042)	(0.039)	(0.037)
	[3.309]	[3.305]	[3.364]	[3.299]	[3.387]	[3.464]
Panel B. Major choice						
Undeclared	-0.017	-0.036**	-0.020**	-0.029	-0.034*	
	(0.011)	(0.017)	(0.009)	(0.027)	(0.020)	
	[0.105]	[0.155]	[0.032]	[0.155]	[0.075]	[0.000]
STEM	0.035***	0.051***	0.037**	0.064**	0.054*	0.053*
	(0.013)	(0.019)	(0.019)	(0.029)	(0.032)	(0.027)
	[0.289]	[0.321]	[0.307]	[0.294]	[0.336]	[0.292]
Business	-0.000	-0.001	-0.004	-0.004	-0.002	-0.000
	(0.005)	(0.008)	(0.008)	(0.015)	(0.015)	(0.015)
	[0.046]	[0.050]	[0.055]	[0.076]	[0.080]	[0.089]
Social sciences	-0.002	0.002	0.007	-0.013	0.001	0.001
	(0.012)	(0.017)	(0.015)	(0.027)	(0.030)	(0.025)
	[0.162]	[0.219]	[0.168]	[0.231]	[0.243]	[0.198]
Humanities/Art	-0.022*	-0.026**	-0.046**	-0.021	-0.034	-0.056*
	(0.013)	(0.013)	(0.019)	(0.020)	(0.023)	(0.030)
	[0.293]	[0.144]	[0.339]	[0.143]	[0.164]	[0.312]
Other	0.006	0.010	0.020*	0.009	0.012	0.010
	(0.008)	(0.011)	(0.011)	(0.017)	(0.019)	(0.019)
	[0.086]	[0.085]	[0.081]	[0.071]	[0.075]	[0.079]
Double major	-0.001	0.000	0.006	-0.006	0.001	-0.009
	(0.005)	(0.008)	(0.006)	(0.013)	(0.012)	(0.011)
	[0.019]	[0.027]	[0.019]	[0.029]	[0.027]	[0.030]
N	3581	2187	2197	888	889	895

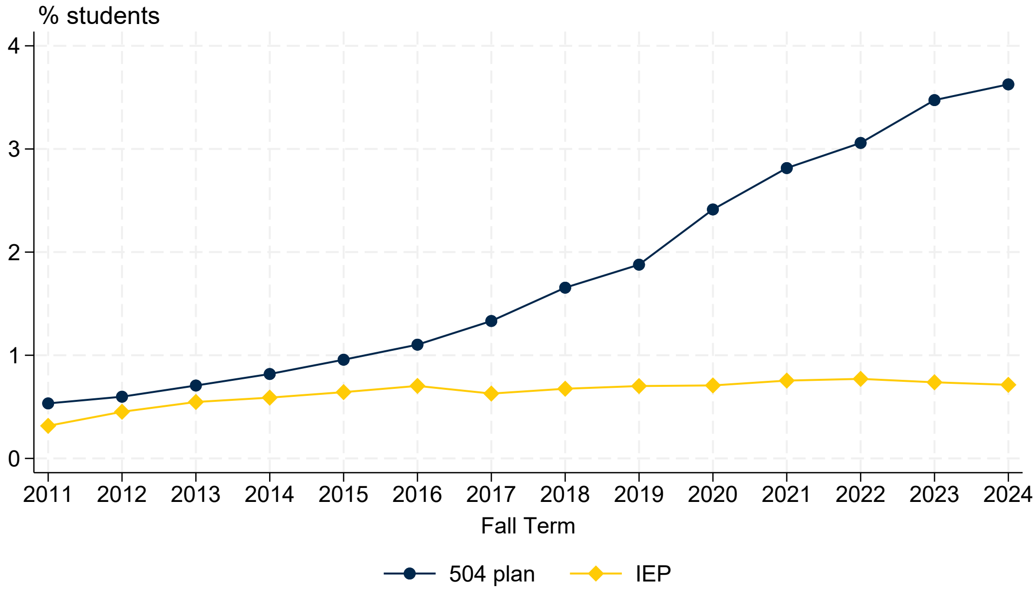
Notes: * p<0.1, ** p<0.05, *** p<0.01. This table uses student x semester data from Fall 2021-Winter 2025 to estimate the impact of accommodations on student long-run academic outcomes (from semester of application). See equation 2 for details. Outcomes are measured for students who are enrolled one, two, or three years out or have graduated. Semester GPAs is the average semester GPA over one, two, and three years or up until graduation (whichever is shorter), excluding the semester of application. Major choice are point-in-time outcomes and are mutually exclusive. If a student double majored in STEM and another field they are coded as majoring in STEM. All other double major categories are coded as "double major". The sample in column 1 includes students applying in Fall 2021-Winter 2024, the sample in columns 2-3 includes students applying in Fall 2021-Winter 2023, and the sample in columns 4-6 includes students applying in Fall 2021-Winter 2022. Controls include cohort x semester FE and the following controls: gender, race, gender, race, household income, high school GPA, SAT scores, number of AP classes, lagged cumulative GPA, lagged indicators for athlete status and major declared, major type, home college (Arts & Sciences, Business, Engineering), and an indicator for applying in a non-enrolled semester. We impute pre-accommodations variables with zeroes and include an indicator for first semester. We use robust standard errors. Control means are in brackets.

Figures

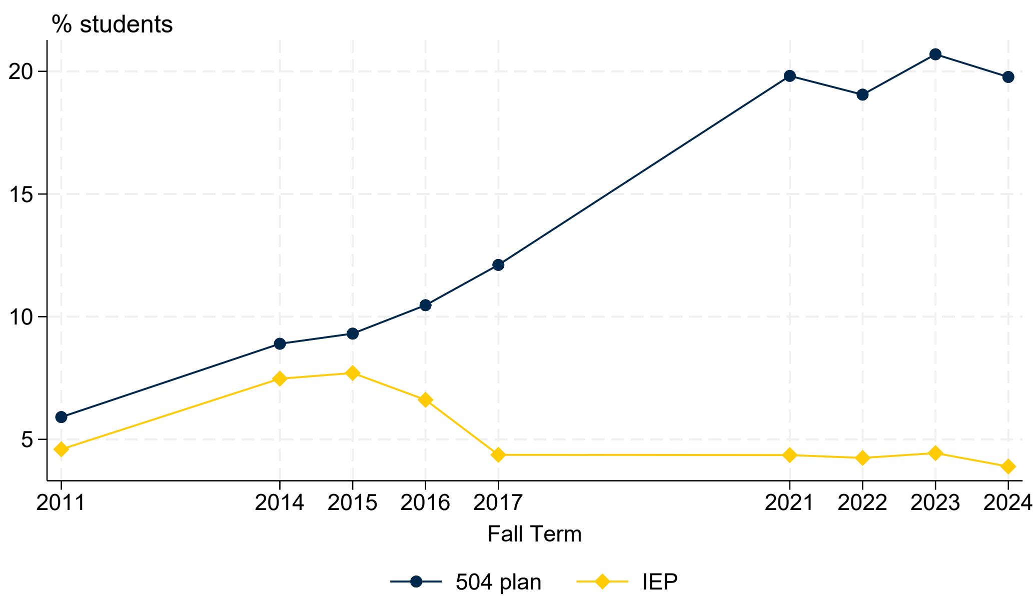


Notes: This figure shows the percentage of students approved for accommodations during each semester. The dashed line represents the best fit line using data prior to 2021.

Figure 1. Trends in Accommodation Usage



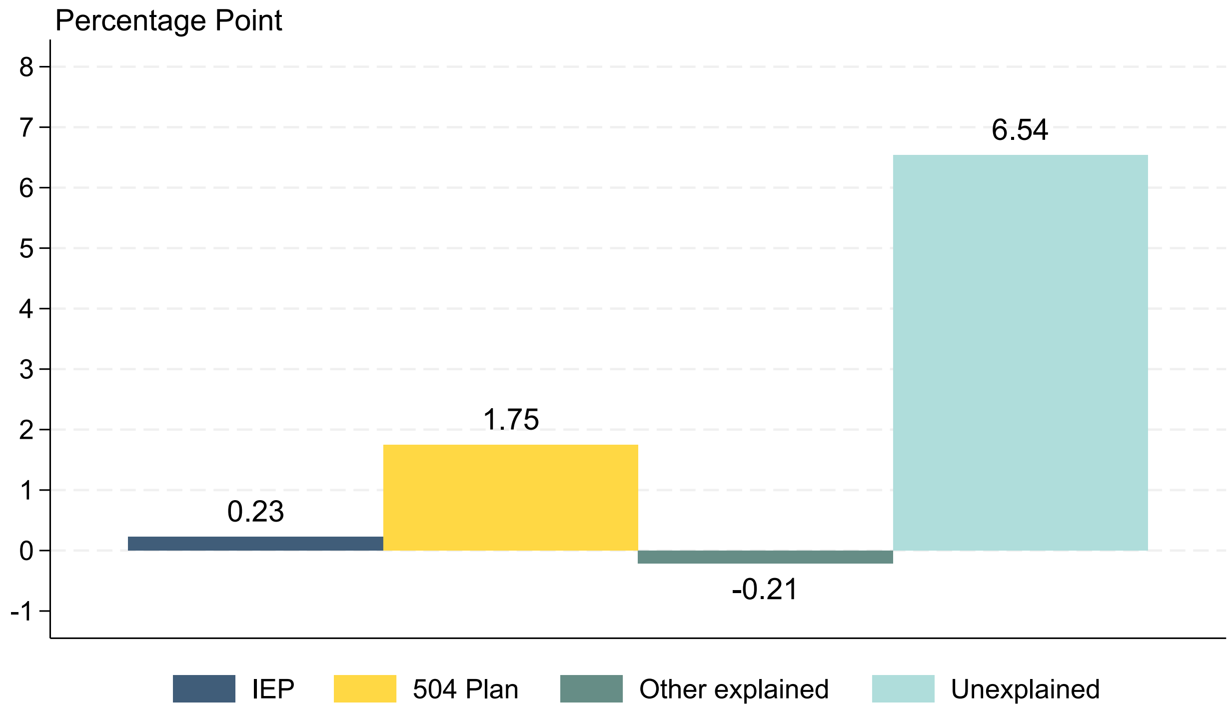
(a) In-State Students



(b) In-State Students Approved for Accommodations

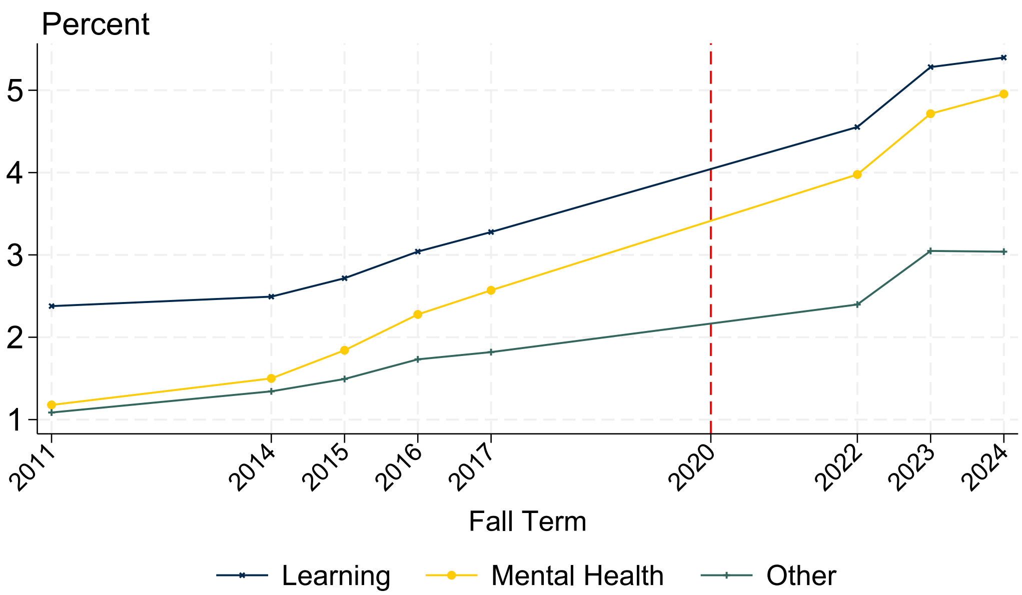
Notes: These are compositional trends for students who had IEP plans, 504 plans, and did not have plans in high school. Panel A presents results for the whole sample and panel B is restricted to students approved for accommodations. If a student had both an IEP and 504 plan, they are coded as having an IEP plan.

Figure 2. Trends in Composition of In-State Students

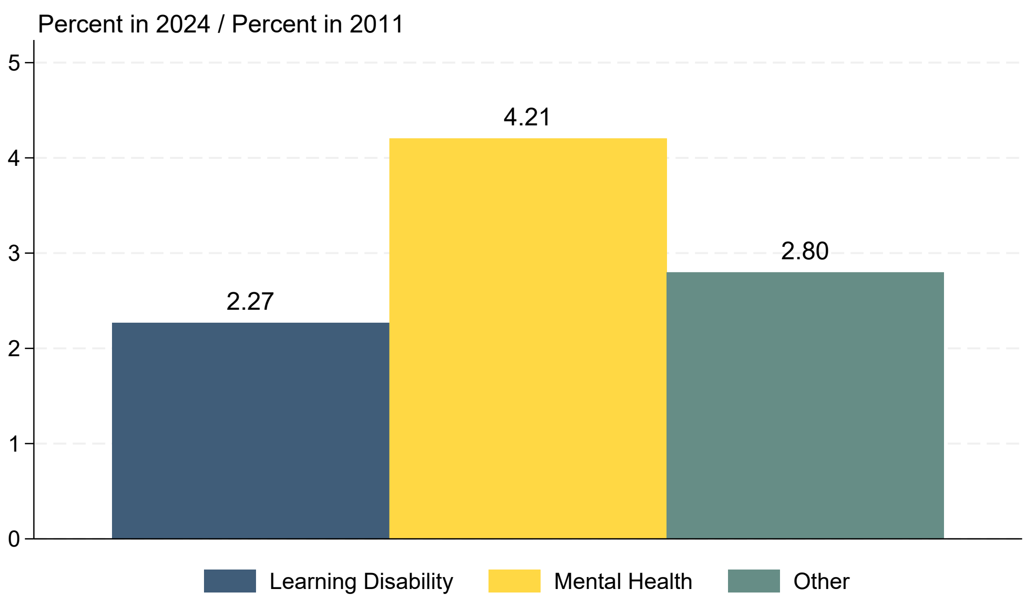


Notes: This figure shows the result of a Oaxaca-Blinder decomposition, where the two two groups are the starting cohorts of Fall 2011 and Fall 2021. Each bar represents how much the observable or unobservable characteristics explain change in the outcome (ever is observed being approved accommodations). We restrict our analysis to in-state students. The outcome variable is whether a student ever uses accommodations in college and the predictors include student demographics (gender, race, family income, and prior achievement) and prior disability status. To estimate the contribution of IEPs and 504 plans, we take the mean change in observable characteristics across the two cohorts and multiply it by the estimated effect of the observable characteristic.

Figure 3. Decomposing Accommodations Growth Across Fall 2011 and 2021 Cohorts



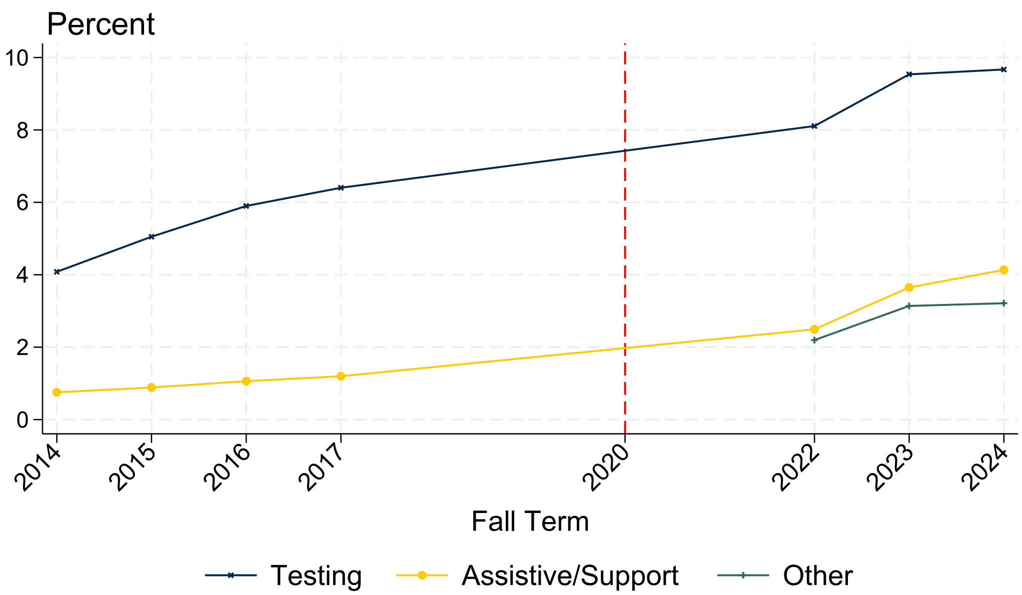
(a) Trends in Disability Reported



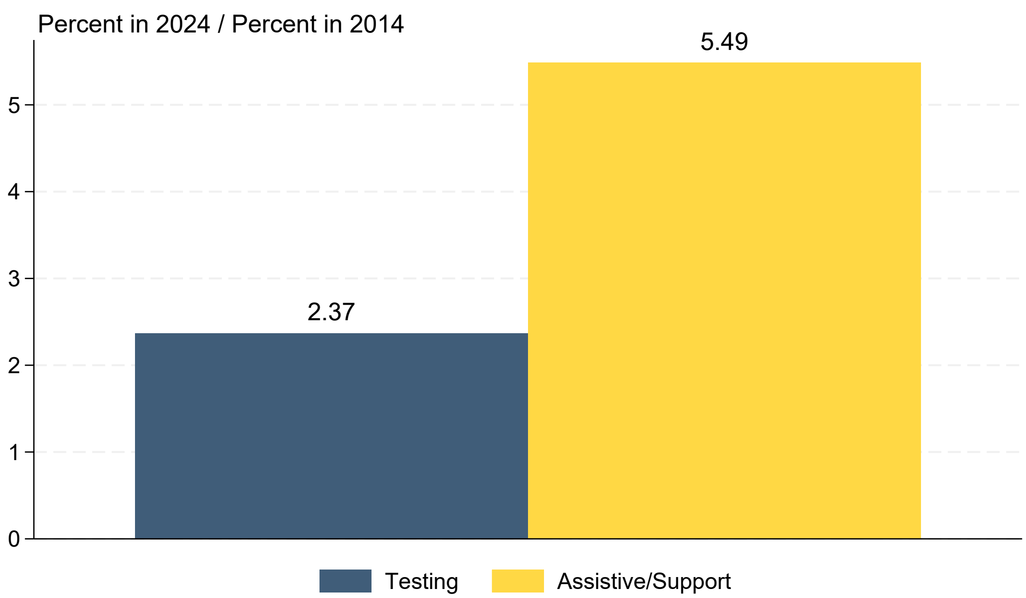
(b) Growth in Accommodated Disabilities Between Fall 2011 and Fall 2024

Notes: Panel A shows trends in the reported disabilities of students (denominator is overall student body). We have incomplete data from Fall 2018–Winter 2021. Disability categories are not mutually exclusive. Learning disabilities include ADHD and intellectual disabilities; mental health includes anxiety, depression, and other psychological conditions; other includes Autism, chronic health conditions (e.g., diabetes, epilepsy), physical disabilities (e.g., vision or hearing impairments), and other disabilities (e.g., speech). Panel B presents the ratio of the share of students with each disability in 2024 over the 2011 share.

Figure 4. Trends in Disability Reported



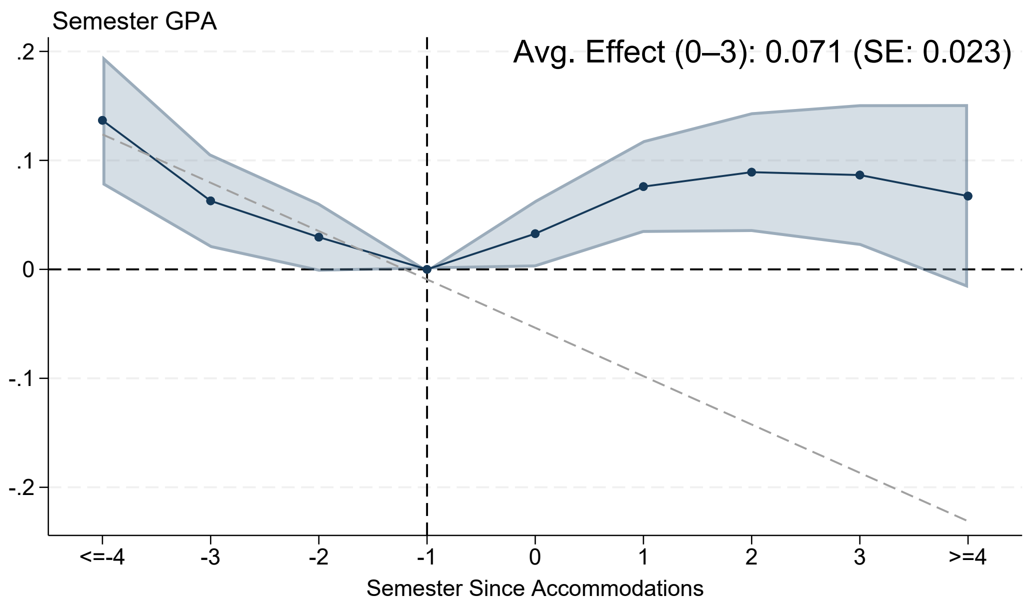
(a) Trends in Accommodations Students are Approved for



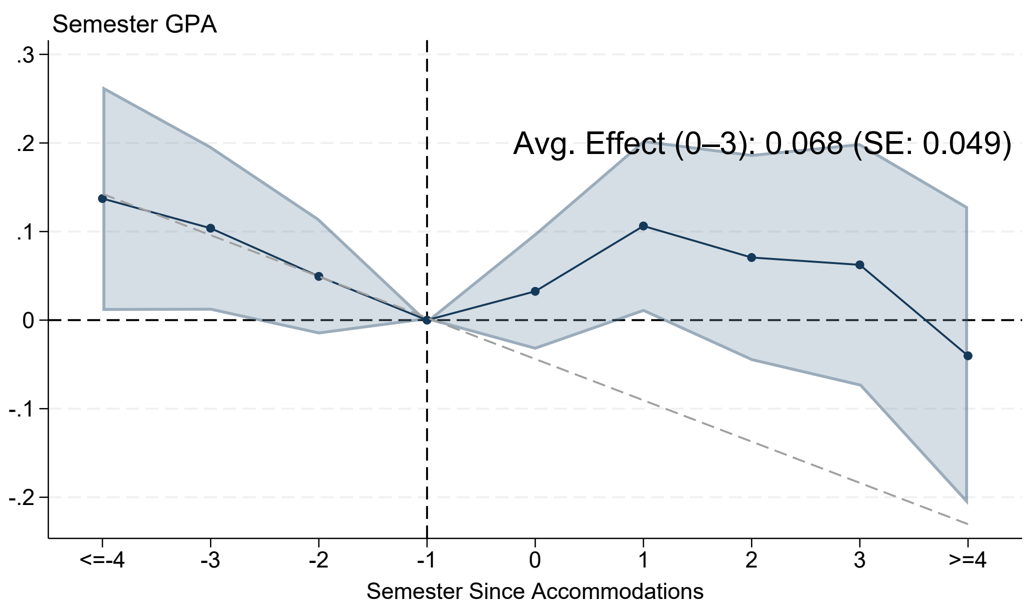
(b) Trends in Accommodations Used

Notes: Panel A shows trends in approved accommodations (denominator is overall student body). We have incomplete data from Fall 2018–Winter 2021. Testing includes extended test time and separate locations. Assistive technology includes the use of note-takers, audio-visual supports, laptops, etc. We are unable to distinguish between different types of accommodations in 2011, so we exclude that year. Panel B presents the ratio of the share of students with each accommodation in 2024 over the 2014 share.

Figure 5. Trends in Disability Reported and Accommodations Used



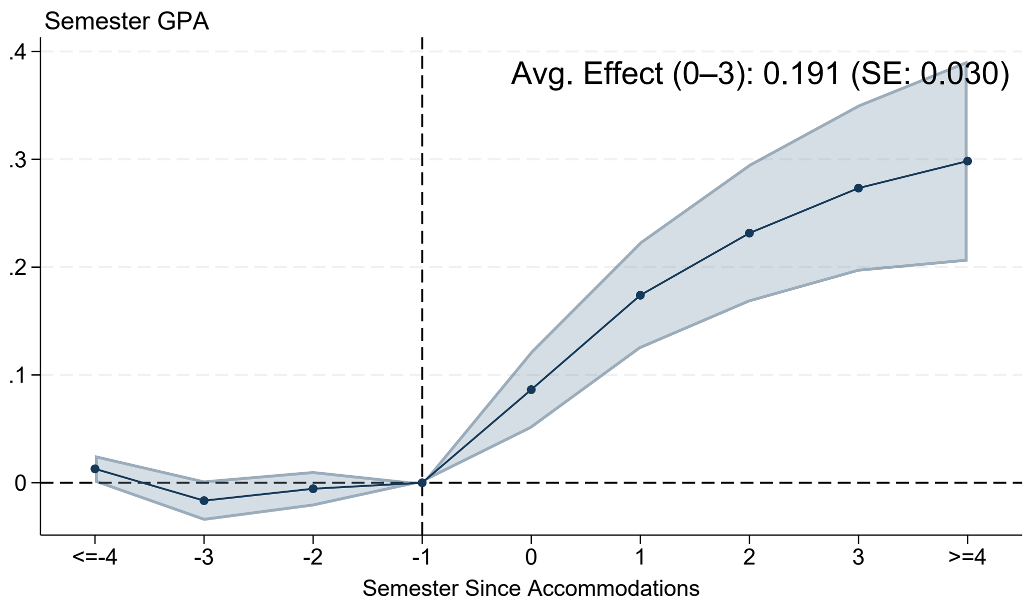
(a) Event Study of Accommodations Approval



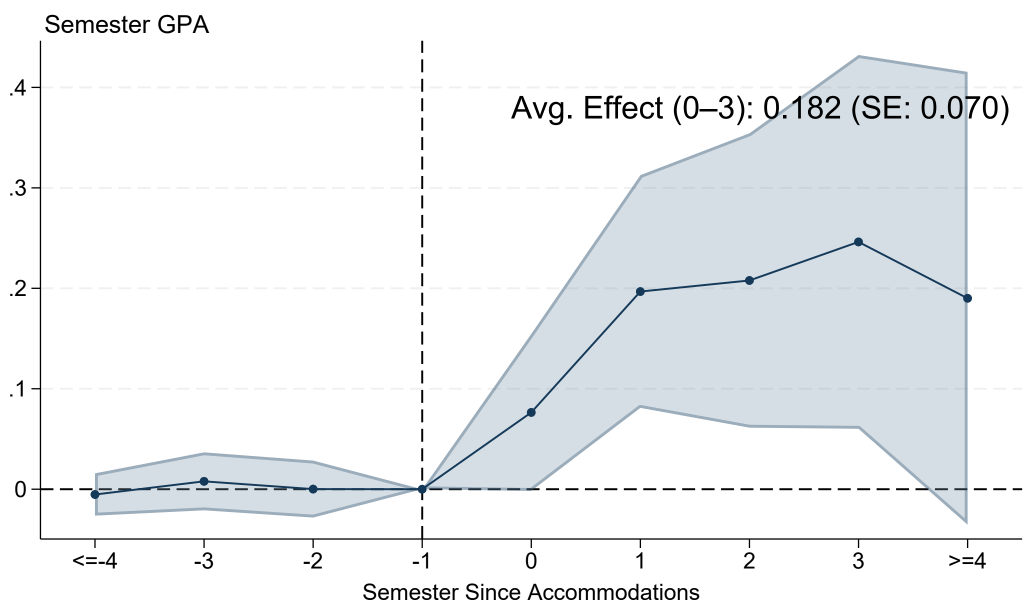
(b) Event Study of Accommodations Approval (At Least 3 Pre/Post Periods)

Notes: This figure shows event study plots of the effect of accommodations approval on current semester GPA for students who were approved for accommodations in the first semester they applied. Controls include student and college entry cohort x semester of application FE. The gray line is the pre-treatment period trend. The sample includes students from Fall 2021-Winter 2025.

Figure 6. Event Study of Accommodations Approval



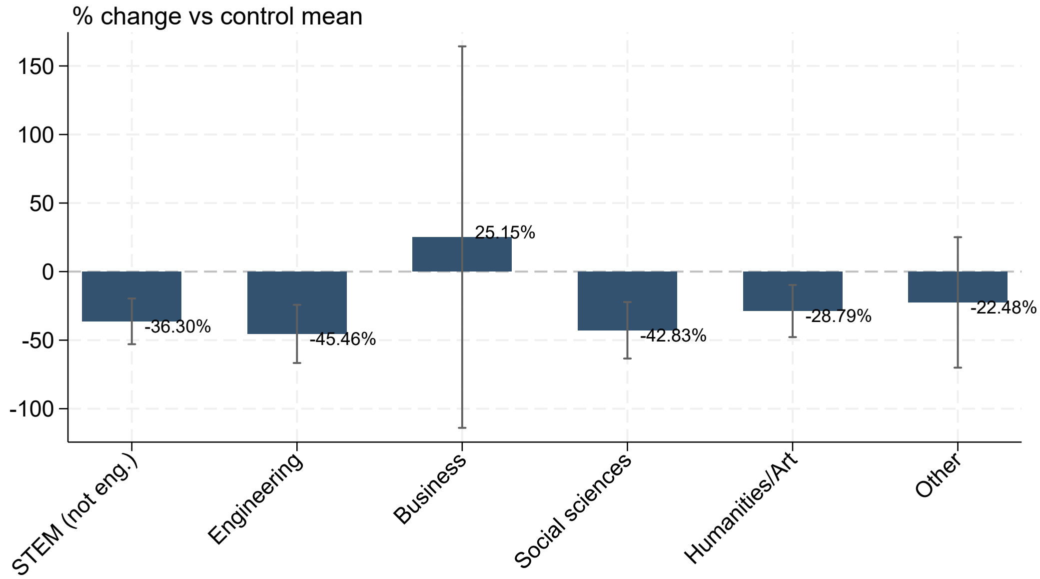
(a) Event Study of Accommodations Approval



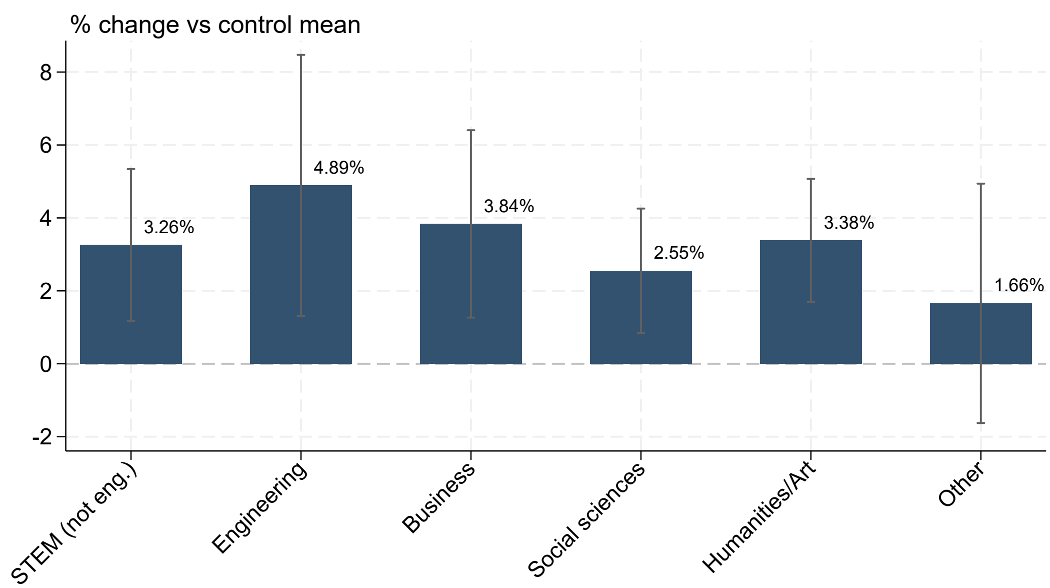
(b) Event Study of Accommodations Approval (At Least 3 Pre/Post Periods)

Notes: This figure shows event study plots of the effect of accommodations approval on current semester GPA for students who were approved for accommodations in the first semester they applied. Controls include student and college entry cohort x semester of application FE. We detrend the plot by subtracting the pre-treatment "effect" from all estimates. Standard errors and confidence intervals are calculated via bootstrapping.

Figure 7. Event Study of Accommodations Approval (De-trended)



(a) Course Withdrawal



(b) Course Grade

Notes: This figure shows the effect of accommodations approval on course-level outcomes among applicants in the semester of application/approval (see equation 3) by course type. In panel A, the outcome is course withdrawal, which is a binary indicator. In panel B, the outcome is course grade, which is on a 0-4 scale based on letter grade (A+/A = 4; A- = 3.7; B+ = 3.4; B = 3; B- = 2.7; C+ = 2.4; C = 2; C-=1.7; D+ = 1.4; D = 1; D- = 0.7; F = 0). Controls include cohort x semester FE and the following individual-level controls: gender, race, gender, race, household income, high school GPA, SAT scores, number of AP classes, lagged cumulative GPA, lagged indicators for athlete status and major declared, major type, initial college (Arts & Sciences, Engineering, and Business), and an indicator for applying in a non-enrolled semester. We include a course fixed effects and control for the leave-one-out share of students approved for accommodations in the course. Standard errors are clustered at the student level and the 95th-percentile CIs are shown.

Figure 8. Effect of Accommodations on Course-level Outcomes

Appendix A Tables

Table A1. Disability Policies

Law	Schooling level	Definition of disability	Services offered
Individuals with Disabilities Education Act (IDEA)	K-12	A child is considered disabled if they fall into 1 of 13 disability categories: Autism, deaf-blindness, deafness, emotional disturbance, hearing impairment, intellectual disability, multiple disabilities, orthopedic impairment, other health impairments, specific learning disabilities, speech or language impairments, traumatic brain injury, or visual impairments.	Individualized instruction through an individualized education plan (IEP). This is applicable for public school students, though a student with disabilities may be provided funds and placed in a non-public school as part of their IEP.
Section 504 of the Rehabilitation Act of 1973	K-12 and postsecondary	Individuals with disabilities are defined as persons with a physical or mental impairment which substantially limits one or more major life activities. Major life activities include caring for one's self, walking, seeing, hearing, speaking, breathing, working, performing manual tasks, and learning.	Schools provide accommodations (e.g., audiobooks, note-taking aids, or extended time to complete tests/assignments) so that a student with a disability has equal access to the general education curriculum. Students do not receive individualized instruction. This law applies to all institutions receiving public funding, including school lunch programs or student loans.

Table A2. Summary Statistics For Students

	(1)	(2)
	Out-of-state	In-state
Ever interacted with disability office	0.13	0.14
Ever approved for accommodations	0.10	0.10
Female	0.51	0.53
Asian	0.30	0.19
Black	0.04	0.05
Hispanic	0.13	0.07
White	0.39	0.59
Other	0.14	0.10
International	0.20	0.00
In-state	0.00	1.00
HH Income <$50K	0.11	0.16
HH Income $50-100K	0.11	0.19
HH Income $100-200K	0.16	0.28
HH Income $200K+	0.33	0.22
HH Income Missing	0.29	0.15
First-gen	0.13	0.18
HS GPA	3.85	3.91
SAT	1443.37	1402.96
Total APs	4.20	3.81
College of Arts & Sciences	0.46	0.52
College of Engineering	0.14	0.15
College of Business	0.07	0.05
College Other	0.33	0.28
N	31775	30358

Notes: This table provide summary statistics for students enrolled from Fall 2021 to Winter 2025. SAT is on a scale of 0-1600. A student is flagged as ever interacting with the disability office if they are ever observed in the Accommodate system (i.e., filled out intake form and requested at least one meeting). APs = Advance Placement courses. Colleges are based on initial college at entry. The college of arts and sciences includes students studying the humanities, social sciences, and natural sciences; engineering includes all engineering majors; business is the undergraduate business program; other covers undergraduate programs outside these three (e.g., nursing; music, theater, and dance; art and design; information; kinesiology; public health; architecture).

Table A3. Institution Characteristics

Panel A. Student Demographics (%)	Study College	Other Colleges	Other Public Colleges	Other Selective Public Colleges
Female	50.13	57.21	54.77	55.78
White Non-Hispanic	58.39	56.77	54.74	37.99
Black Non-Hispanic	4.33	12.91	13.62	17.56
Hispanic Any Race	6.42	13.31	15.39	23.23
Asian, Nat. Hawaiian, or Pac. Isl.	14.63	4.71	5.56	10.28
Native American	0.11	0.68	1.02	0.26
Disability (%)	7.00	8.67	6.40	5.89
Disability $< 3\%$	0.00	52.67	45.42	51.95
Panel B. Institutional Characteristics				
Full-time Tuition and Fees (out-of-State)	51082.00	26489.49	21104.27	22742.90
Acceptance Rate (%)	22.83	68.40	70.93	37.13
Fall 2018 Enrollment	29084.00	3567.96	8847.71	12106.62
SAT Math 75th Pctl	780.00	609.20	603.88	648.39
SAT Reading 75th Pctl	730.00	613.10	606.33	638.96
ACT Math 75th Pctl	34.00	25.37	25.20	27.49
ACT English 75th Pctl	35.00	26.30	25.83	28.93
N	1	2,007	557	77

Notes: This table reports the means of Fall 2018 school characteristics, comparing Study College with other undergraduate institutions. Race, ethnic, and gender demographics are for full-time undergraduate degree-seeking students. Disability refers to the Percentage of undergraduates, who are formally registered as students with disabilities, when percentage is greater than 3 percent. The percent of colleges with less than 3 percent of formally registered students with disabilities are also reported. Public College are any institutions whose listed as a Public, four-year or above institution. Selective College is defined as having an acceptance rate below 50%. The sample consists of colleges where their female share and acceptance rates were reported in 2018. Source: IPEDS/Urban Institute.

Table A4. Summary Statistics

	(1)	(2)	(3)	(4)
	Out-of-state		In-state	
	Never Accommodations	Ever Accommodations	Never Accommodations	Ever Accommodations
Female	0.49	0.63	0.52	0.68
Asian	0.32	0.12	0.20	0.10
Black	0.04	0.04	0.05	0.06
Hispanic	0.12	0.16	0.07	0.08
White	0.38	0.56	0.58	0.63
Other	0.14	0.12	0.10	0.12
International	0.21	0.06	0.00	0.00
HH Income <$50K	0.11	0.11	0.15	0.20
HH Income $50-100K	0.11	0.08	0.19	0.17
HH Income $100-200K	0.17	0.12	0.29	0.25
HH Income $200K+	0.32	0.39	0.22	0.23
HH Income Missing	0.28	0.29	0.15	0.16
HS GPA	3.86	3.83	3.91	3.88
SAT	1444.35	1438.34	1405.84	1380.63
Total APs	4.26	3.64	3.92	2.88
N	28217	3271	27557	3088

Notes: This table provide summary statistics for students enrolled from Fall 2021 to Winter 2025. SAT is on a scale of 0-1600. APs = Advance Placement courses.

Table A5. Predicting Accommodations Usage for In-State Students by IEP/504 in HS

	(1)	(2)	(3)	(4)	(5)	(6)
	Ever Accommodations (0/1)					
	IEP/504 Plan			No IEP/504 Plan		
Female	0.105***	0.039**	0.032*	0.057***	0.009***	0.008***
	(0.034)	(0.020)	(0.019)	(0.003)	(0.002)	(0.002)
Asian	-0.009	-0.043	-0.041	-0.036***	-0.005**	-0.005**
	(0.065)	(0.038)	(0.037)	(0.004)	(0.003)	(0.003)
Black	0.154	0.018	-0.001	-0.006	-0.004	-0.004
	(0.104)	(0.060)	(0.059)	(0.008)	(0.005)	(0.005)
Hispanic	0.034	0.005	-0.006	0.009	0.006	0.003
	(0.066)	(0.038)	(0.037)	(0.007)	(0.004)	(0.004)
Other	-0.012	0.015	0.007	0.015***	0.005	0.004
	(0.056)	(0.032)	(0.032)	(0.006)	(0.003)	(0.003)
First-gen	-0.079	0.019	0.023	-0.008*	-0.007**	-0.006**
	(0.056)	(0.032)	(0.032)	(0.005)	(0.003)	(0.003)
HH income $50-100k	-0.047	-0.020	-0.025	-0.026***	-0.002	-0.001
	(0.064)	(0.037)	(0.036)	(0.006)	(0.003)	(0.003)
HH income $100-200k	0.007	0.001	-0.005	-0.031***	0.001	0.001
	(0.059)	(0.034)	(0.033)	(0.006)	(0.003)	(0.003)
HH income $200k+	0.079	0.030	0.032	-0.018***	0.006*	0.007*
	(0.062)	(0.036)	(0.035)	(0.006)	(0.004)	(0.004)
HH income missing	0.075	0.059	0.060	-0.022***	0.007*	0.008**
	(0.066)	(0.038)	(0.038)	(0.006)	(0.004)	(0.004)
HS GPA	0.037	0.146*	0.153*	-0.101***	0.010	0.010
	(0.138)	(0.080)	(0.078)	(0.016)	(0.010)	(0.009)
SAT (std)	0.016	0.009	0.009	0.004***	0.003***	0.003***
	(0.017)	(0.010)	(0.009)	(0.002)	(0.001)	(0.001)
Total APs	-0.017***	-0.009**	-0.007**	-0.003***	-0.000	-0.000
	(0.006)	(0.003)	(0.003)	(0.001)	(0.000)	(0.000)
Applied		0.833***	0.769***		0.684***	0.567***
		(0.020)	(0.022)		(0.003)	(0.004)
Documentation submitted			0.159***			0.292***
			(0.025)			(0.005)
N	907	907	907	29437	29437	29437
R-squared	0.097	0.698	0.712	0.033	0.651	0.683
Outcome mean	0.520	0.520	0.520	0.096	0.096	0.096

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table present results from a linear probability model, where the outcome is a binary indicator that is equal to 1 if a student ever used accommodations and 0 otherwise. The sample includes students enrolled from Fall 2021-Winter 2025. All regressions include starting semester fixed effects. Column 1-3 consists of in-state students who had an IEP/504 plan in HS. Columns 4-6 consist of in-state students who did not have an IEP/504 plan in HS. Applied is an indicator for requesting a meeting with the disability office. Documentation submitted is an indicator for whether a student submitted a documentation during their initial meeting request. We use robust standard errors.

Table A6. Short-Run Impact of Academic Accommodations (Course-Level)

	(1) Course withdrawal	(2) Class grade (0-4)	(3) Pr(A)	(4) Pr(B)	(5) Pr(C)	(6) Pr(D)	(7) Pr(F)
Panel A. Course-level outcomes without peer controls							
Approved	-0.029***	0.115***	0.065***	-0.034***	-0.020***	-0.005*	-0.003
	(0.004)	(0.018)	(0.010)	(0.010)	(0.006)	(0.003)	(0.004)
N	30668	17558	17558	17558	17558	17558	17558
Control mean	0.048	3.498	0.653	0.251	0.073	0.012	0.007
Panel B. Course-level outcomes with peer controls							
Approved	-0.029***	0.115***	0.065***	-0.034***	-0.020***	-0.005*	-0.003
	(0.004)	(0.018)	(0.010)	(0.010)	(0.006)	(0.003)	(0.004)
Share accommodated	0.051	-0.297	-0.019	-0.061	-0.084	0.104**	0.011
	(0.076)	(0.339)	(0.210)	(0.196)	(0.113)	(0.052)	(0.087)
N	30668	17558	17558	17558	17558	17558	17558
Control mean	0.048	3.498	0.653	0.251	0.073	0.012	0.007
Panel C. Course-level outcomes with peer controls and interaction							
Approved	-0.025***	0.076**	0.039**	-0.020	-0.012	0.001	-0.003
	(0.009)	(0.037)	(0.020)	(0.018)	(0.011)	(0.005)	(0.006)
* share accommodated	-0.074	0.684	0.461	-0.257	-0.135	-0.090	-0.008
	(0.120)	(0.536)	(0.285)	(0.262)	(0.160)	(0.073)	(0.108)
Share accommodated	0.104	-0.793	-0.352	0.125	0.014	0.169**	0.017
	(0.125)	(0.537)	(0.296)	(0.279)	(0.165)	(0.077)	(0.119)
N	30668	17558	17558	17558	17558	17558	17558
Control mean	0.048	3.498	0.653	0.251	0.073	0.012	0.007

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table uses student x semester x course data from Fall 2021-Winter 2025 to estimate the impact of accommodations on student short-run academic outcomes (semester of application). Course grades are only observed for courses students did not withdraw from. For column 2, course grades are converted from letter grades: A+/A=4, A–=3.7, B+=3.4, B=3, B–=2.7, C+=2.4, C=2, C–=1.7, D+=1.4, D=1, D–=0.7, F=0. We compare students who are approved for accommodations to students that are not approved (see equation 3). Share accommodated is the leave-one-out share of accommodated peers. Controls include cohort x semester FE and the following controls: gender, race, gender, race, household income, high school GPA, SAT scores, number of AP classes, lagged cumulative GPA, lagged indicators for athlete status and major declared, major type, initial college (Arts & Sciences, Engineering, Business, and other), and an indicator for applying in a non-enrolled semester. For this analysis, we impute pre-accommodations variables with zeroes and include missing indicator for first semester of attendance. We cluster standard errors at the student level.

Table A7. Short-Run Impact of Academic Accommodations Heterogeneity

	(1) Withdrawal semester (0/1)	(2) # course withdrawals	(3) GPA	(4) #As	(5) #Bs	(6) #Cs	(7) #Ds	(8) #Fs
Out-of-state	-0.027***	-0.154***	0.092***	0.181**	-0.048	-0.036	-0.021	-0.010
	(0.007)	(0.034)	(0.029)	(0.076)	(0.052)	(0.027)	(0.013)	(0.014)
In-state	-0.032***	-0.151***	0.124***	0.181***	-0.026	0.013	-0.006	-0.057***
	(0.007)	(0.036)	(0.030)	(0.068)	(0.048)	(0.030)	(0.012)	(0.016)
Male	-0.046***	-0.153***	0.178***	0.270***	-0.095	-0.064*	-0.025	-0.048**
	(0.010)	(0.043)	(0.038)	(0.089)	(0.064)	(0.039)	(0.016)	(0.021)
Female	-0.024***	-0.153***	0.086***	0.162***	0.000	0.003	-0.011	-0.024**
	(0.005)	(0.031)	(0.025)	(0.061)	(0.042)	(0.024)	(0.011)	(0.012)
White	-0.021***	-0.114***	0.092***	0.173**	-0.036	-0.018	-0.021*	-0.038***
	(0.006)	(0.031)	(0.026)	(0.067)	(0.048)	(0.028)	(0.012)	(0.014)
Asian	-0.042**	-0.212***	0.143**	0.266*	-0.143	0.049	-0.026	-0.067***
	(0.016)	(0.080)	(0.056)	(0.141)	(0.101)	(0.047)	(0.026)	(0.026)
Black	-0.012	-0.060	0.165	0.378*	-0.083	0.112	-0.074	-0.056
	(0.021)	(0.118)	(0.116)	(0.221)	(0.175)	(0.101)	(0.062)	(0.064)
Hispanic	0.004	-0.122*	0.157**	0.220	0.006	-0.078	0.012	-0.034
	(0.008)	(0.064)	(0.072)	(0.164)	(0.115)	(0.066)	(0.026)	(0.033)
Other	-0.046***	-0.206**	0.113	0.223	0.035	-0.131**	0.012	0.034
	(0.016)	(0.092)	(0.079)	(0.178)	(0.120)	(0.065)	(0.022)	(0.047)
HH income <$50K	-0.029**	-0.228***	0.155**	0.205	0.169*	-0.059	0.036	-0.048
	(0.013)	(0.070)	(0.062)	(0.128)	(0.092)	(0.060)	(0.027)	(0.034)
HH income $50-100K	-0.056***	-0.173**	0.131**	0.191	0.062	0.023	-0.062*	-0.054
	(0.017)	(0.078)	(0.061)	(0.140)	(0.092)	(0.067)	(0.033)	(0.036)
HH income $100-200K	-0.019**	-0.066	0.186***	0.430***	-0.017	-0.091*	-0.041*	-0.055**
	(0.008)	(0.058)	(0.052)	(0.123)	(0.082)	(0.054)	(0.022)	(0.024)
HH income $200K+	-0.022***	-0.126***	0.020	-0.138	-0.008	0.021	-0.008	-0.016
	(0.008)	(0.043)	(0.033)	(0.099)	(0.069)	(0.031)	(0.013)	(0.014)
HH income missing	-0.016*	-0.113**	0.106**	0.391***	-0.289***	0.011	-0.002	-0.013
	(0.010)	(0.051)	(0.046)	(0.115)	(0.083)	(0.043)	(0.019)	(0.023)
Control mean	0.050	0.305	3.334	2.383	0.975	0.313	0.063	0.048
P-value for out-of-state = in-state	0.615	0.805	0.365	0.652	0.954	0.326	0.247	0.063
P-value for male = female	0.040	0.687	0.195	0.593	0.396	0.170	0.661	0.344
P-value for white = asian	0.116	0.264	0.514	0.824	0.621	0.510	0.813	0.365
P-value for white = black	0.712	0.454	0.845	0.940	0.399	0.102	0.864	0.786
P-value for white = hispanic	0.034	0.904	0.911	0.842	0.687	0.279	0.024	0.196
P-value for white = other	0.021	0.112	0.721	0.834	0.897	0.308	0.046	0.221
P-value for hh income <$50K = $50-100K	0.098	0.760	0.755	0.386	0.111	0.730	0.006	0.987
P-value for hh income <$50K = $100-200K	0.763	0.175	0.271	0.084	0.221	0.455	0.004	0.619
P-value for hh income <$50K = $200k+	0.563	0.619	0.175	0.151	0.074	0.390	0.041	0.207
P-value for hh income <$50K = missing	0.609	0.469	0.938	0.111	0.000	0.832	0.031	0.269

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table uses student x semester data from Fall 2021-Winter 2025 to estimate the impact of accommodations on student short-run academic outcomes (semester of application). Column 1: term withdrawal (binary, observed only for students who initially enroll that term). Column 2: number of course withdrawals (observed only for students enrolled in at least one course). Columns 3–8: grade outcomes (observed only for graded, non–pass/fail courses). This table compares students who are approved for accommodations to students that are not approved (see equation 2, where controls include cohort x semester FE and the following controls: gender, race, gender, race, household income, high school GPA, SAT scores, number of AP classes, lagged cumulative GPA, lagged indicators for athlete status and major declared, major type, home college (Arts & Sciences, Business, Engineering), an indicator for applying in a non-enrolled semester. This regression is run separately by subgroup. For this analysis, we impute pre-accommodations variables with zeroes and include missing indicator for first semester of attendance. We use robust standard errors.

Table A8. Long-Run Impact of Academic Accommodations on GPA and Major Choice, Testing for Compositional Change by Initial College

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	College of Engineering						College of Arts and Sciences					
	Graduated or observed in data for at least...											
	1 year	2 years		3 years			1 year	2 years		3 years		
Outcome measured:	One year	One year	Two year	One year	Two year	Three year	One year	One year	Two year	One year	Two year	Three year
Panel A. Academic performance												
Semester GPAs (avg)	0.220***	0.280***	0.239***	0.154	0.053	0.035	0.090***	0.053	0.049	0.066	0.040	0.041
	(0.066)	(0.089)	(0.074)	(0.113)	(0.112)	(0.103)	(0.030)	(0.034)	(0.032)	(0.061)	(0.055)	(0.052)
Panel B. Major choice												
Undeclared	-0.093***	-0.161***	-0.063**	-0.147*	-0.117*		-0.005	-0.004	-0.022*	-0.016	-0.049	
	(0.031)	(0.048)	(0.031)	(0.081)	(0.064)		(0.015)	(0.024)	(0.013)	(0.038)	(0.030)	
STEM	0.094**	0.164***	0.120**	0.116	0.063	0.048	0.021	0.028	0.001	0.043	0.022	0.024
	(0.036)	(0.057)	(0.052)	(0.092)	(0.077)	(0.070)	(0.017)	(0.025)	(0.025)	(0.040)	(0.046)	(0.038)
Business	-0.008	-0.015	-0.031	0.004	0.005		-0.000	-0.004	-0.006	-0.022	-0.018	-0.021
	(0.009)	(0.014)	(0.022)	(0.013)	(0.013)		(0.005)	(0.006)	(0.007)	(0.016)	(0.016)	(0.016)
Social sciences	0.009	0.025	0.002	0.015	0.038	0.028	0.001	0.012	0.019	0.015	0.040	0.040
	(0.014)	(0.025)	(0.019)	(0.020)	(0.030)	(0.025)	(0.017)	(0.026)	(0.022)	(0.043)	(0.047)	(0.038)
Humanities/Art	-0.008	-0.013	-0.018			-0.087	-0.005	-0.025	-0.018	-0.012	-0.019	-0.040
	(0.014)	(0.012)	(0.029)			(0.058)	(0.014)	(0.017)	(0.023)	(0.023)	(0.031)	(0.042)
Other	0.007	0.000	-0.010	0.011	0.011	0.011	-0.005	-0.040	0.002	0.005	0.017	0.007
	(0.006)	(0.004)	(0.010)	(0.015)	(0.015)	(0.015)	(0.010)	(0.042)	(0.013)	(0.021)	(0.025)	(0.024)
Double major							-0.007	-0.009	0.008	-0.013	0.007	-0.010
							(0.007)	(0.011)	(0.009)	(0.019)	(0.018)	(0.016)
N	511	289	289	121	121	121	2347	1352	1352	559	559	559

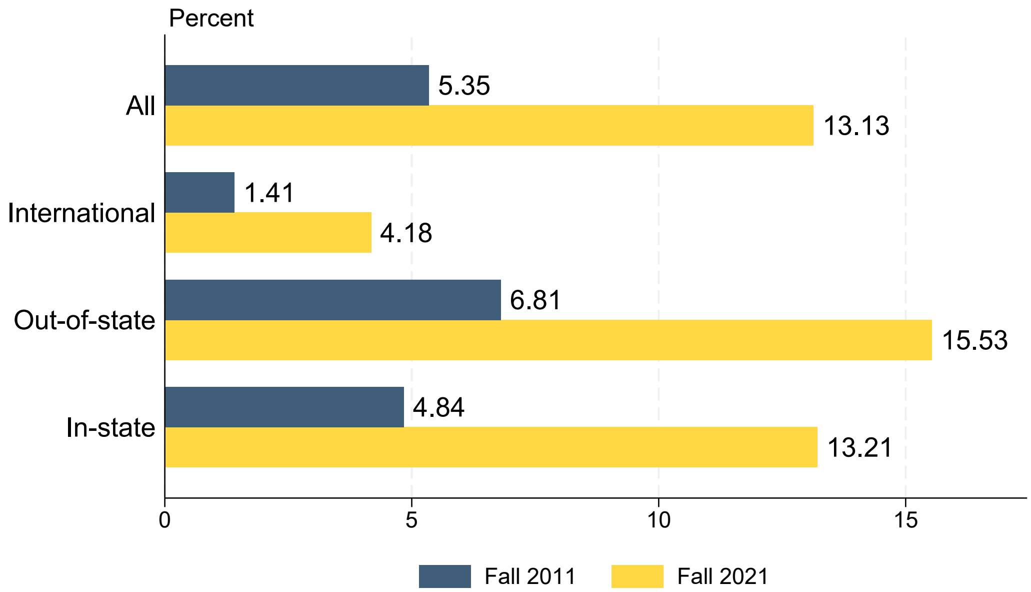
Notes: * p<0.1, ** p<0.05, *** p<0.01. This table uses student x semester data from Fall 2021-Winter 2025 to estimate the impact of accommodations on student long-run academic outcomes (from semester of application) by initial college. See equation 2 for details. Outcomes are measured for students who are enrolled one or two years out or have graduated. Semester GPAs is the average semester GPA over one or two years or up until graduation (whichever is shorter), excluding the semester of application. If a student double majored in STEM and another field they are coded as majoring in STEM. All other double major categories are coded as "double major". The sample in columns 1 and 7 includes students applying in Fall 2021-Winter 2024, the sample in columns 2-3 and 8-9 includes students applying in Fall 2021-Winter 2023, and the sample in columns 4-6 and 10-12 includes students applying in Fall 2021-Winter 2022. Controls include cohort x semester FE and the following controls: gender, race, gender, race, household income, high school GPA, SAT scores, number of AP classes, lagged cumulative GPA, lagged indicators for athlete status and major declared, major type, home college (Arts & Sciences, Business, Engineering), and an indicator for applying in a non-enrolled semester. We impute pre-accommodations variables with zeroes and include an indicator for first semester. We use robust standard errors.

Table A9. Long-Run (One Year) Impact of Academic Accommodations Heterogeneity

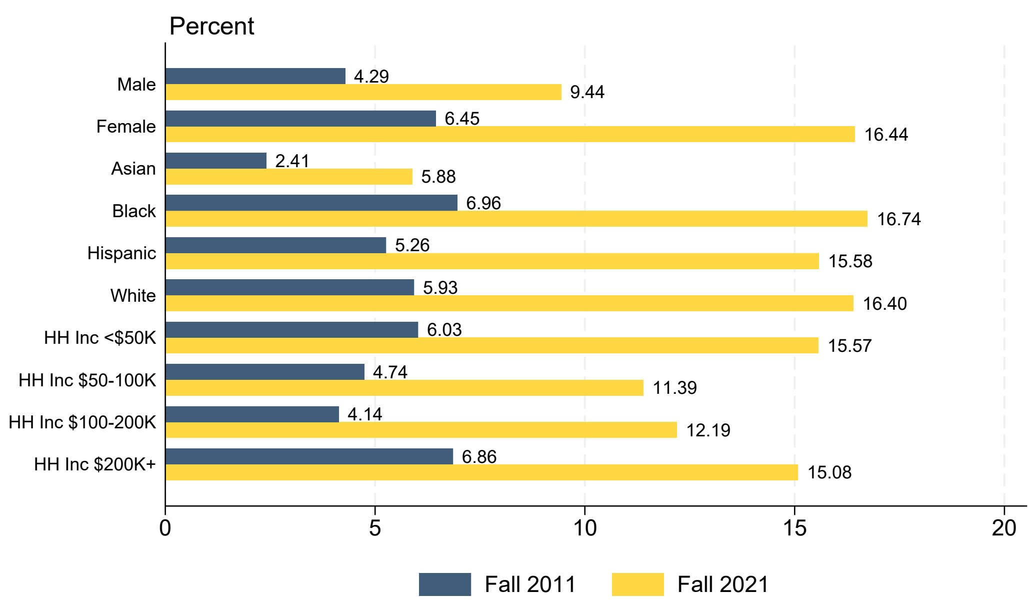
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Subgroup	Enrolled in semester	Graduated	Cum. credits earned	Semester GPAs (avg)	Undeclared	STEM	Business	Social sciences	Humanities/Art	Other	Double major
Out-of-state	0.040**	0.002	1.279**	0.096***	-0.001	0.019	0.004	-0.033*	-0.028	0.035***	0.002
	(0.019)	(0.013)	(0.565)	(0.030)	(0.015)	(0.020)	(0.007)	(0.017)	(0.020)	(0.013)	(0.006)
In-state	0.059***	-0.003	1.566***	0.098***	-0.030*	0.054***	-0.001	0.016	-0.022	-0.012	-0.005
	(0.017)	(0.014)	(0.503)	(0.034)	(0.016)	(0.019)	(0.007)	(0.016)	(0.017)	(0.010)	(0.008)
Male	0.077***	-0.018	0.909	0.122***	-0.026	0.012	-0.001	0.010	0.013	-0.003	-0.005
	(0.025)	(0.019)	(0.667)	(0.043)	(0.019)	(0.025)	(0.010)	(0.020)	(0.023)	(0.014)	(0.007)
Female	0.027*	0.011	1.782***	0.083***	-0.013	0.051***	0.003	-0.011	-0.046***	0.013	0.004
	(0.015)	(0.011)	(0.456)	(0.027)	(0.013)	(0.016)	(0.006)	(0.015)	(0.016)	(0.010)	(0.006)
White	0.057***	-0.005	1.303***	0.072**	-0.002	0.013	0.000	-0.001	-0.023	0.011	0.001
	(0.018)	(0.013)	(0.502)	(0.030)	(0.015)	(0.018)	(0.005)	(0.016)	(0.017)	(0.011)	(0.007)
Asian	0.046	-0.018	0.801	0.103*	-0.050*	0.084**	-0.001	-0.039	-0.033	0.021	0.018*
	(0.035)	(0.030)	(1.047)	(0.062)	(0.027)	(0.040)	(0.013)	(0.031)	(0.034)	(0.015)	(0.009)
Black	0.005	0.000	2.100	0.100	-0.034	-0.035	0.043	-0.000	0.084	-0.038	-0.019
	(0.077)	(0.050)	(2.329)	(0.140)	(0.065)	(0.080)	(0.032)	(0.091)	(0.083)	(0.051)	(0.021)
Hispanic	0.050	0.019	1.995	0.185***	-0.068**	0.069	0.016	0.039	-0.066	0.033	-0.022
	(0.038)	(0.025)	(1.262)	(0.071)	(0.034)	(0.043)	(0.025)	(0.033)	(0.044)	(0.031)	(0.018)
Other	-0.007	0.015	1.046	0.124	0.022	0.100**	-0.023	-0.042	-0.043	-0.010	-0.003
	(0.045)	(0.030)	(1.192)	(0.085)	(0.034)	(0.049)	(0.024)	(0.043)	(0.051)	(0.034)	(0.011)
HH income <$50K	0.009	0.045	2.258**	0.033	-0.005	0.061*	-0.004	0.013	-0.060*	-0.009	0.003
	(0.033)	(0.028)	(0.981)	(0.061)	(0.028)	(0.034)	(0.006)	(0.032)	(0.033)	(0.019)	(0.015)
HH income $50-100K	0.022	0.014	0.263	0.231***	-0.029	0.046	-0.010	-0.007	0.019	-0.012	-0.008
	(0.040)	(0.030)	(1.092)	(0.073)	(0.031)	(0.035)	(0.016)	(0.030)	(0.034)	(0.024)	(0.008)
HH income $100-200K	0.048*	0.011	1.640*	0.135***	-0.056**	0.020	0.005	0.037	0.004	-0.004	-0.006
	(0.029)	(0.023)	(0.856)	(0.052)	(0.027)	(0.033)	(0.010)	(0.027)	(0.031)	(0.016)	(0.013)
HH income $200K+	0.056**	0.001	0.588	0.054	-0.016	0.051*	0.012	-0.040*	-0.051*	0.028**	0.016**
	(0.023)	(0.017)	(0.640)	(0.036)	(0.021)	(0.026)	(0.016)	(0.023)	(0.027)	(0.014)	(0.007)
HH income missing	0.072**	-0.041**	1.818*	0.087	0.013	0.022	-0.000	-0.009	-0.004	-0.015	-0.007
	0.072**	-0.041**	1.818*	0.087	0.013	0.022	-0.000	-0.009	-0.004	-0.015	-0.007
Control mean	0.715	0.124	18.474	3.309	0.105	0.289	0.046	0.162	0.293	0.086	0.019
P-value for out-of-state = in-state	0.381	0.729	0.842	0.874	0.256	0.101	0.092	0.069	0.470	0.000	0.589
P-value for male = female	0.086	0.446	0.663	0.302	0.664	0.374	0.901	0.278	0.195	0.578	0.147
P-value for white = asian	0.529	0.882	0.649	0.272	0.092	0.165	0.936	0.354	0.856	0.441	0.099
P-value for white = black	0.733	0.955	0.474	0.928	0.663	0.972	0.211	0.684	0.237	0.428	0.453
P-value for white = hispanic	0.294	0.090	0.863	0.790	0.342	0.174	0.691	0.114	0.231	0.624	0.281
P-value for white = other	0.552	0.805	0.560	0.985	0.662	0.283	0.333	0.791	0.735	0.395	0.604
P-value for hh income <$50K = $50-100K	0.944	0.469	0.077	0.012	0.571	0.590	0.490	0.912	0.196	0.453	0.403
P-value for hh income <$50K = $100-200K	0.640	0.389	0.411	0.039	0.123	0.239	0.334	0.322	0.151	0.557	0.464
P-value for hh income <$50K = $200k+	0.348	0.253	0.265	0.276	0.875	0.634	0.162	0.320	0.971	0.154	0.855
P-value for hh income <$50K = missing	0.238	0.022	0.756	0.174	0.229	0.161	0.843	0.820	0.344	0.847	0.325

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table uses student x semester data from Fall 2021-Winter 2025 to estimate the impact of accommodations on student long-run academic outcomes (from semester of application) by different subgroups. See equation 2 for details. Outcomes are measured for students who are enrolled one year out or have graduated. Semester GPAs is the average semester GPA over one, two, and three years or up until graduation (whichever is shorter), excluding the semester of application. Cumulative credits earned is the total number of credits earned between application and one, two, and three years later or up until graduation (whichever is shorter). Major choice are point-in-time outcomes and are mutually exclusive. If a student double majored in STEM and another field they are coded as majoring in STEM. All other double major categories are coded as "double major". Controls include cohort x semester FE and the following controls: gender, race, gender, race, household income, high school GPA, SAT scores, number of AP classes, lagged cumulative GPA, lagged indicators for athlete status and major declared, major type, home college (Arts & Sciences, Business, Engineering), and an indicator for applying in a non-enrolled semester. We impute pre-accommodations variables with zeroes and include an indicator for first semester. We use robust standard errors.

Appendix A Figures



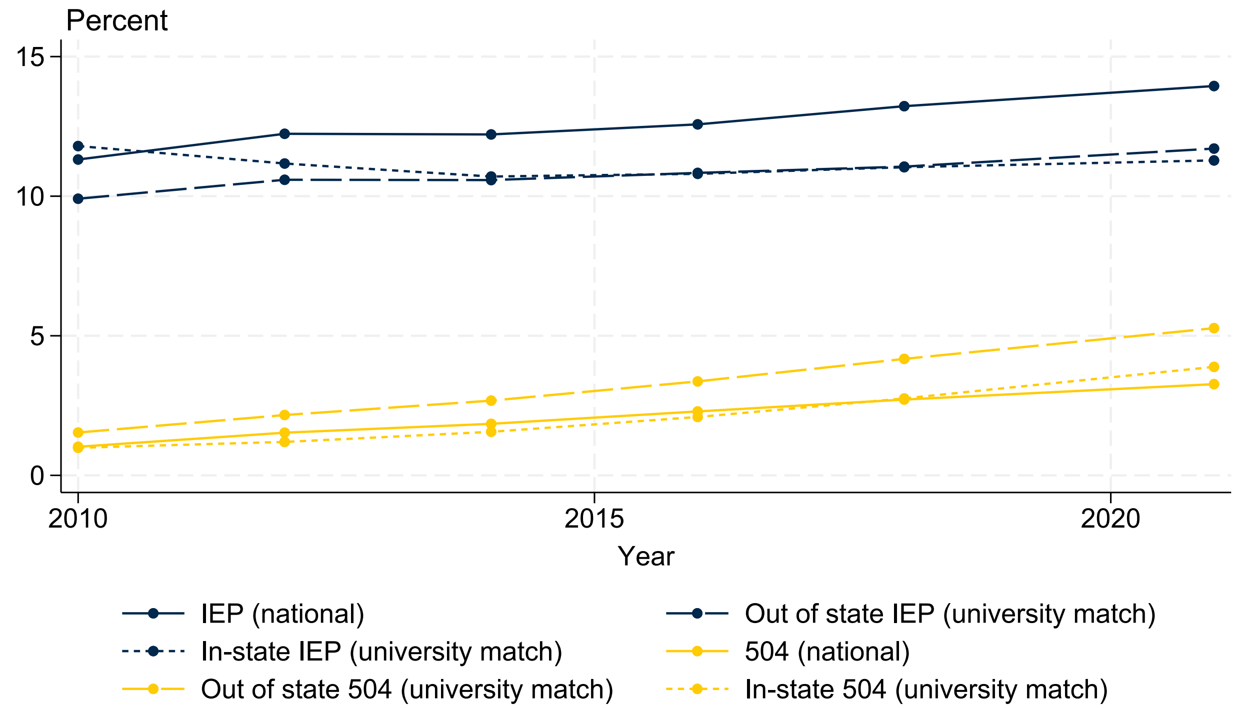
(a) Geography



(b) Student Demographics

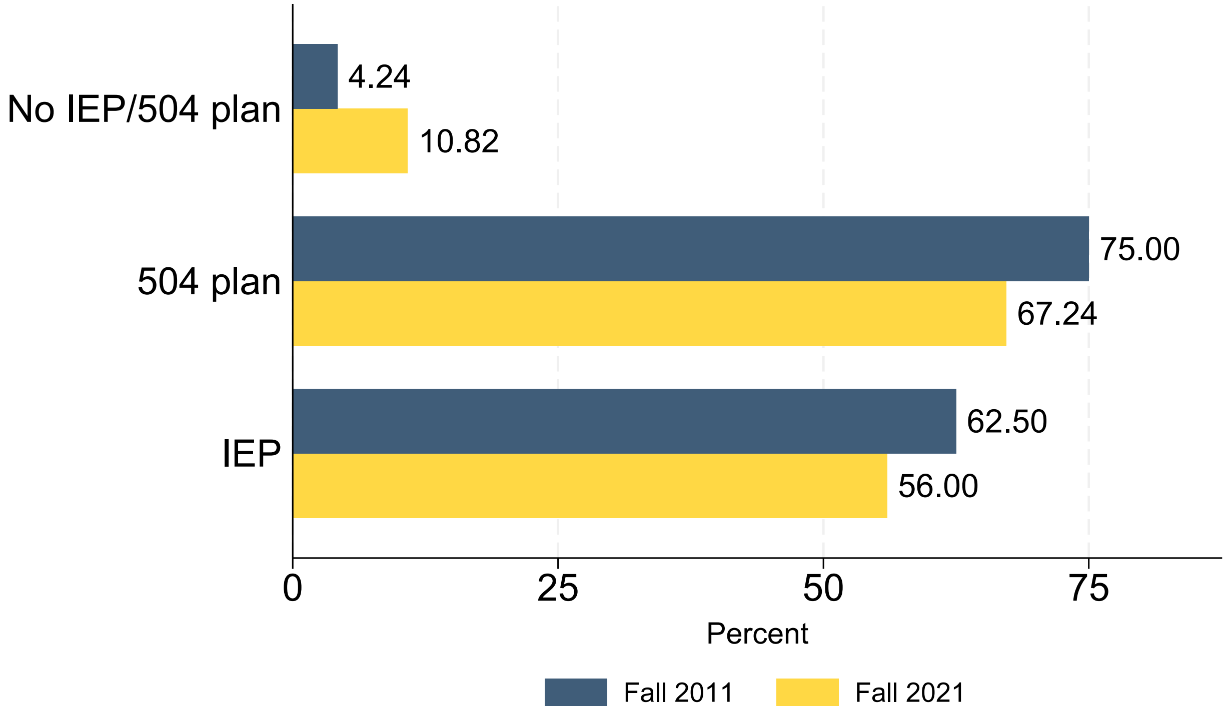
Notes: This figure shows the percent of students who are ever observed using accommodations by starting semester, broken down by different groups.

Figure A1. Percent of Students Who Ever Use Accommodations by Starting Semester



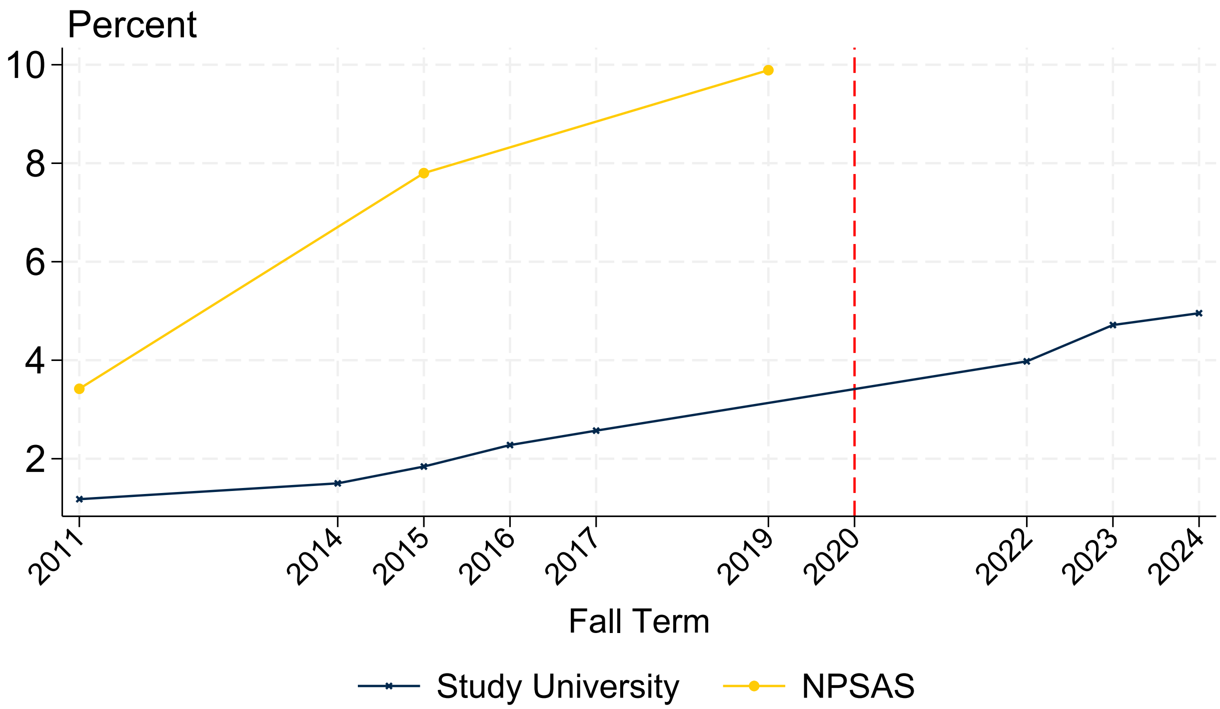
Notes: This figure shows the percentage of high school students with IEP and 504 plans. The dashed lines comprise out-of-state high schools attended by students in our dataset; the dotted lines show in-state high schools. IEP = Individualized Education Program. Source: The Civil Rights Data Collection (CRDC)

Figure A2. Percent of IEP and 504 Students in High School



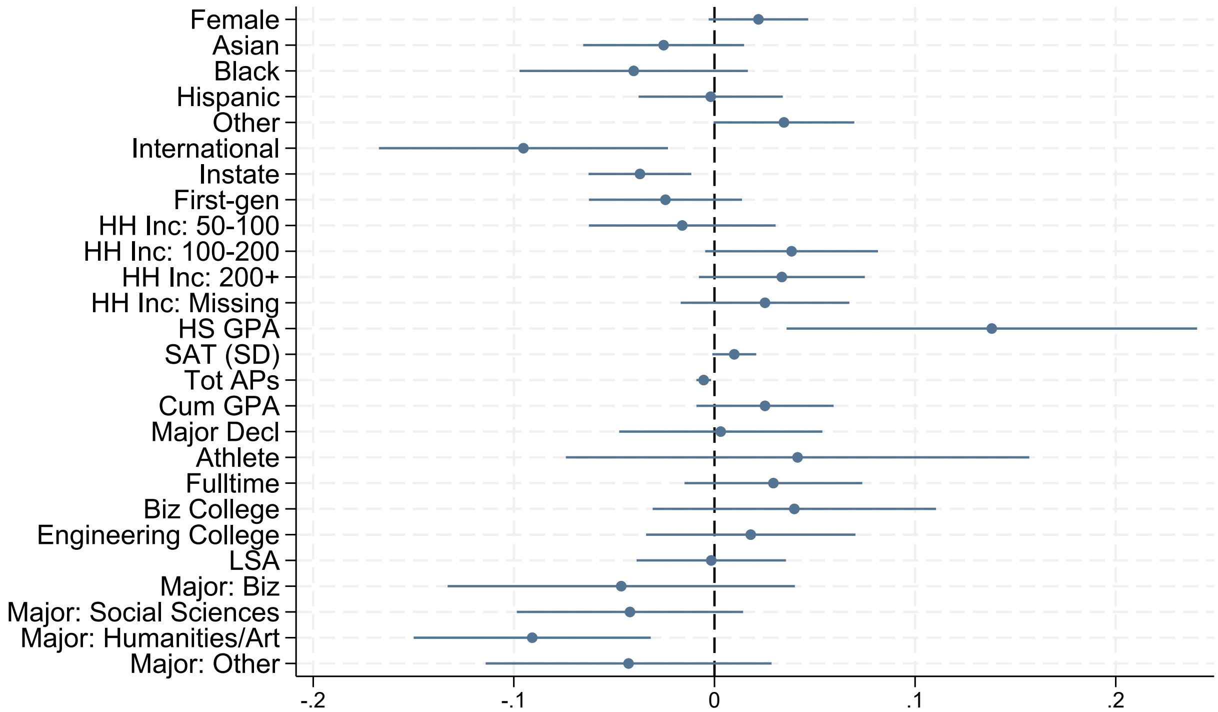
Notes: This figure shows the percentage of students who ever use accommodations by whether or not they had an IEP or 504 plan in high school among in-state students. If a student had both an IEP and 504 plan, they are coded as having an IEP. IEP = Individualized Education Program.

Figure A3. Percent of In-State Students Who Ever Use Accommodations by K-12 Disability Status



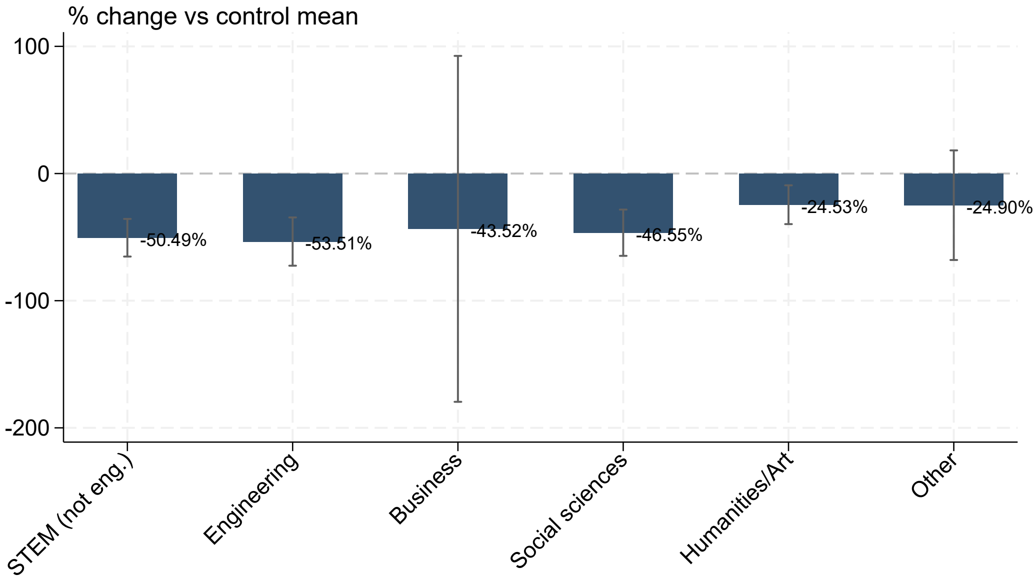
Notes: This figure shows the percentage of students who are approved for accommodations for a mental health condition from our study university and the percentage of students who report having a mental health condition in the National Postsecondary Aid Survey (NPSAS).

Figure A4. Trends in Mental Health Among College Students in Study University and Nationally

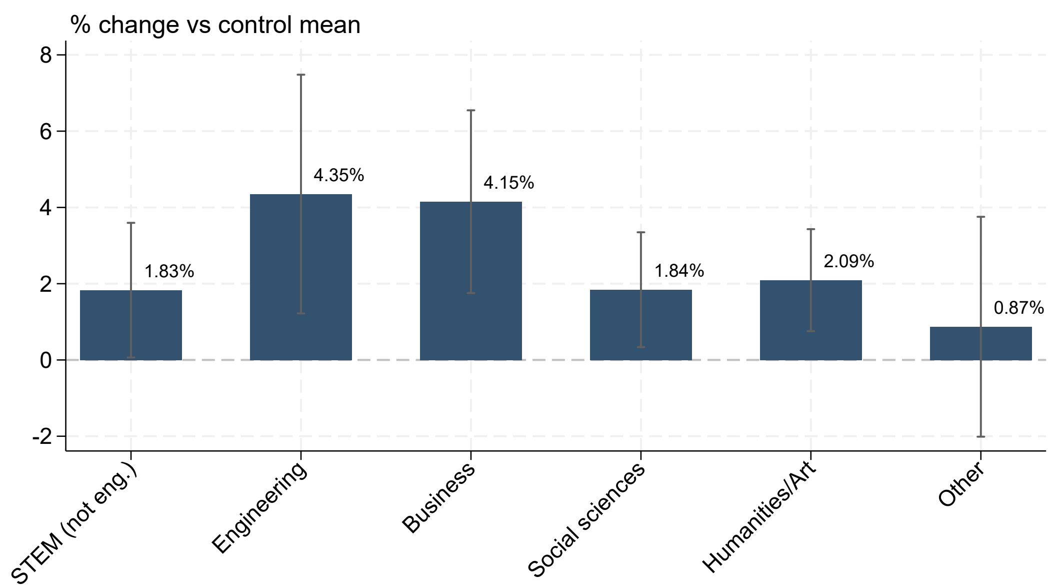


Notes: This figure presents point estimates from a regression, where the outcome is 1 if a student was approved for accommodations in the semester they applied and 0 if the student was approved in the future or never approved. It also includes college entry cohort x semester of application FE, week of semester of application FE, and a binary indicator for if this was a student's first semester in college. All independent college variables are from the semester prior to application. For students applying in their first semester of college, we set these variables to zero and include an indicator for a student's first semester. Robust standard errors are used.

Figure A5. Predicting Approval Probability Among Applicants



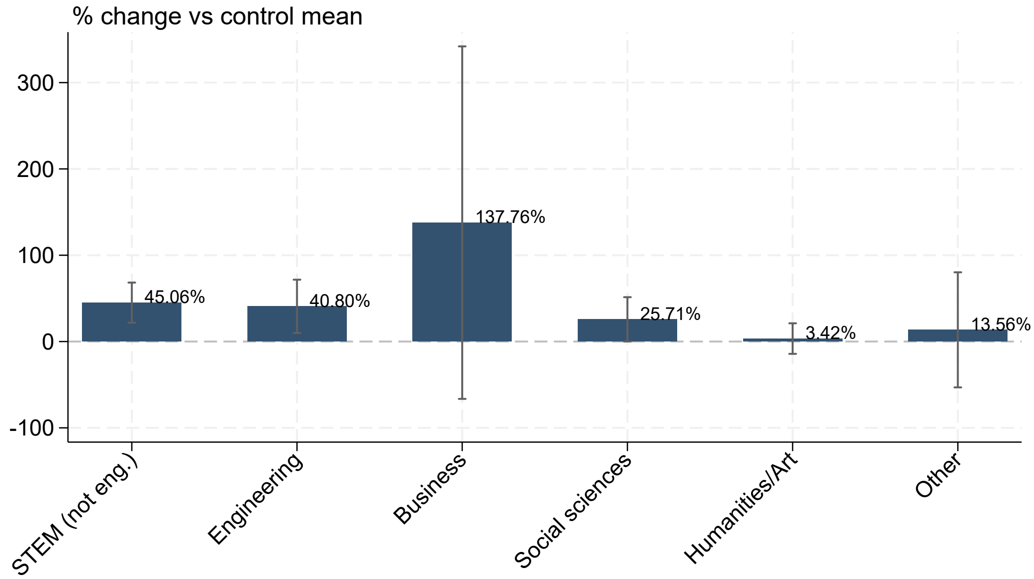
(a) Course withdrawal



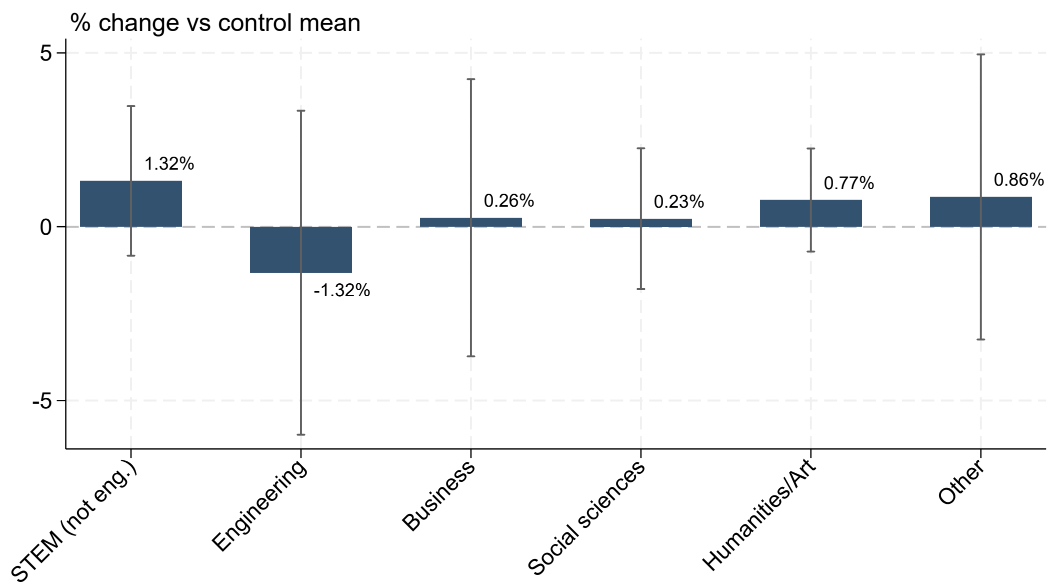
(b) Course grade (0–4)

Notes: This figure estimates the direct-use effect of accommodations by comparing, within the application/approval semester, courses where an approved applicant requested accommodations to courses taken by applicants who were not approved (see equation 3). Panel A reports effects on a course-withdrawal indicator; Panel B reports effects on course grade (0–4 scale: A+/A=4, A–=3.7, B+=3.4, B=3, B–=2.7, C+=2.4, C=2, C–=1.7, D+=1.4, D=1, D–=0.7, F=0). All models include cohort-by-semester fixed effects; individual controls for gender, race/ethnicity, household income, high school GPA, SAT, AP courses, lagged cumulative GPA, athlete status, major declared and major type, initial college (Arts & Sciences, Engineering, Business), and an indicator for applying in a non-enrolled semester; course fixed effects; and the leave-one-out share of approved peers in the course. Standard errors are clustered at the student level; 95% confidence intervals shown.

Figure A6. Direct-Use Effects: Requested Accommodations and Course-Level Outcomes



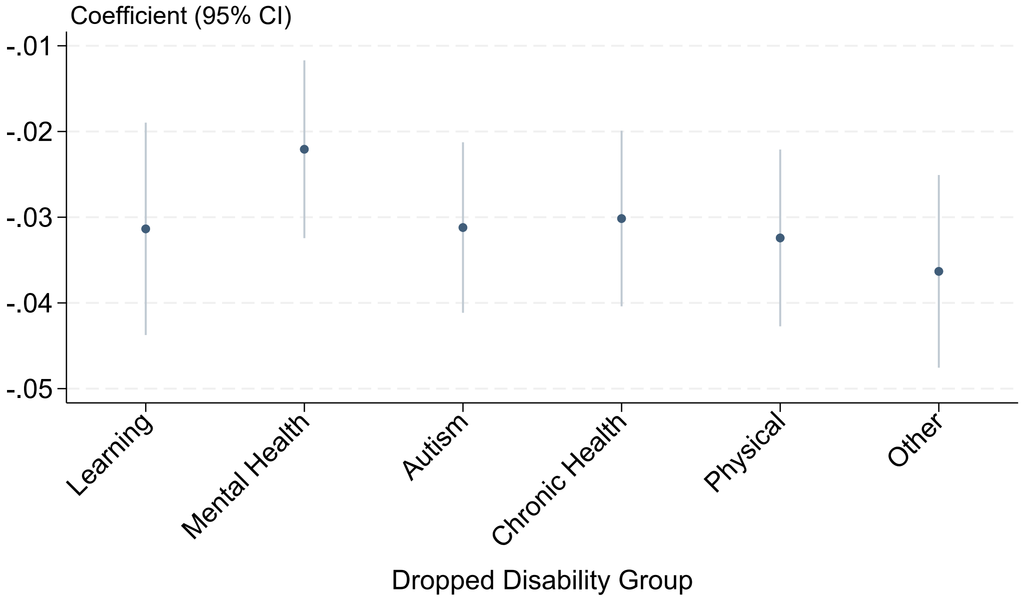
(a) Course withdrawal



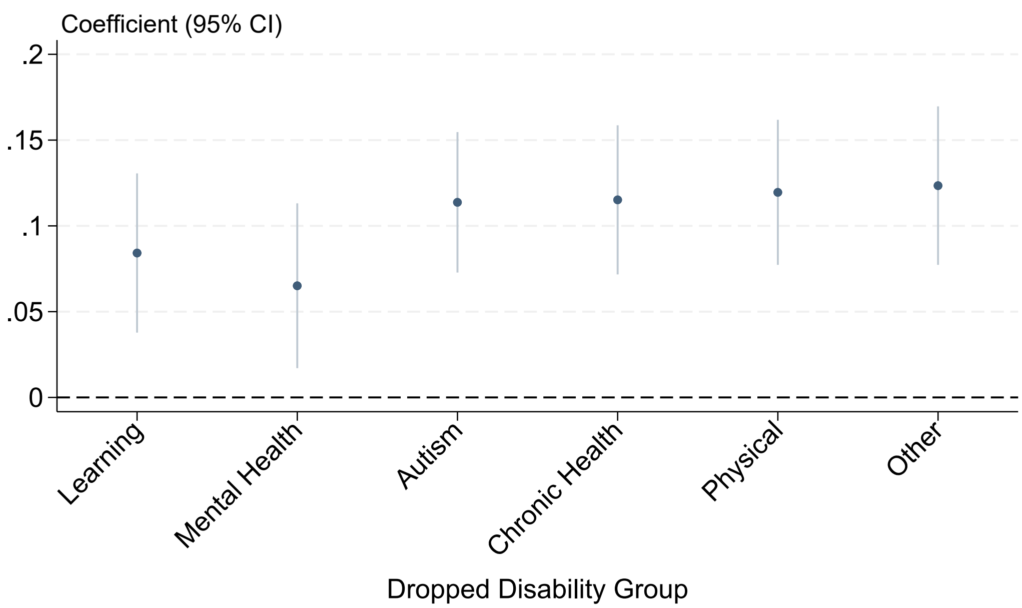
(b) Course grade (0–4)

Notes: This figure estimates potential spillover effects by comparing, within the application/approval semester, courses taken by applicants who were approved for accommodations but did not request them in that course to courses taken by applicants who were not approved (see equation 3). Panel A reports effects on a course-withdrawal indicator; Panel B reports effects on course grade (0–4 scale: A+/A=4, A–=3.7, B+=3.4, B=3, B–=2.7, C+=2.4, C=2, C–=1.7, D+=1.4, D=1, D–=0.7, F=0). Models include cohort-by-semester fixed effects; individual controls for gender, race/ethnicity, household income, high school GPA, SAT, AP courses, lagged cumulative GPA, athlete status, major declared and major type, initial college (Arts & Sciences, Engineering, Business), and an indicator for applying in a non-enrolled semester; course fixed effects; and the leave-one-out share of approved peers in the course. Standard errors clustered at the student level; 95% confidence intervals shown.

Figure A7. Non-Requested Courses: Approved Accommodations and Course-Level Outcomes



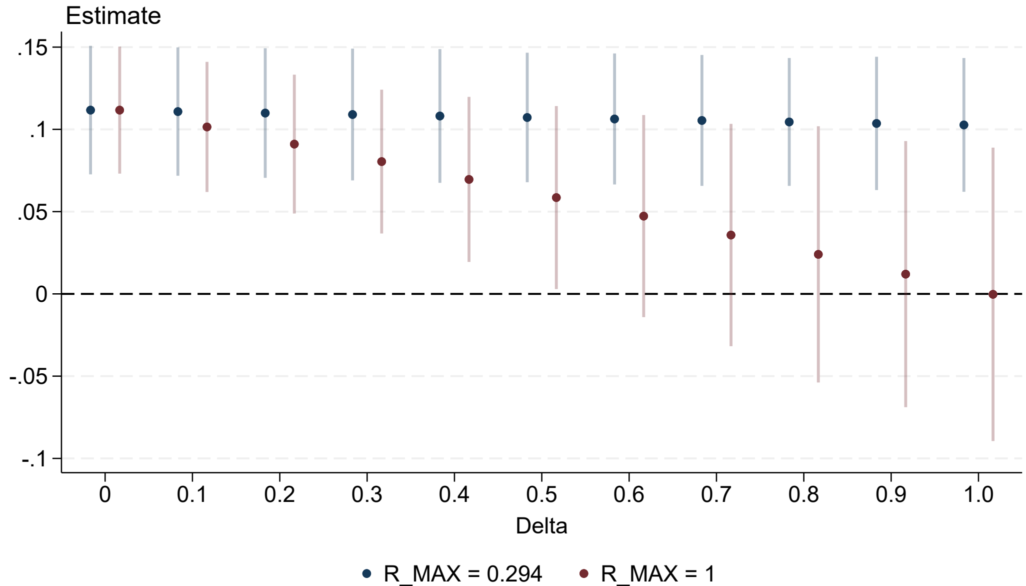
(a) Withdraw From Semester



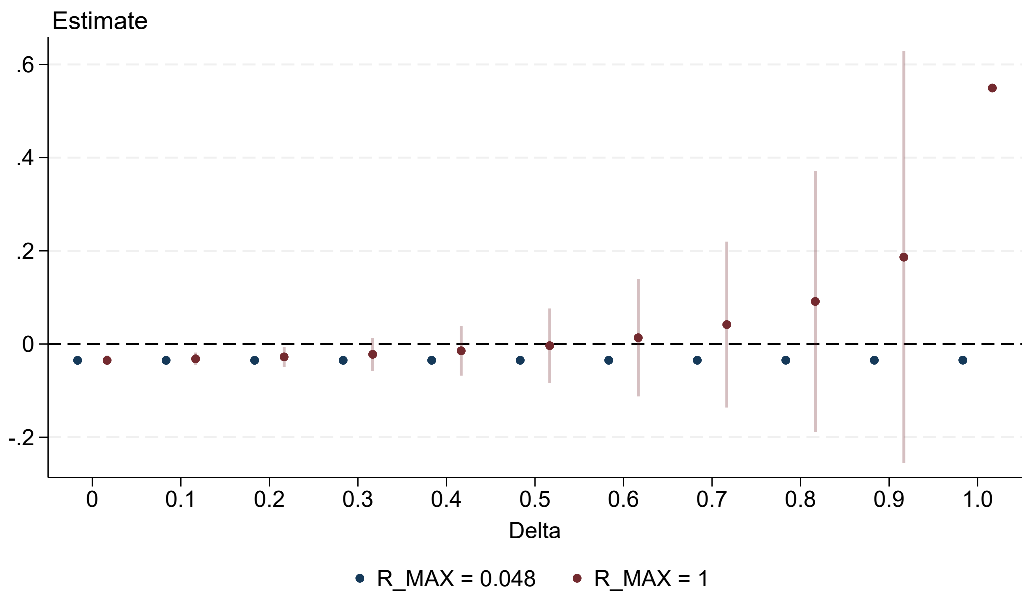
(b) Current Semester GPA

Notes: This figure shows how sensitive treatment effect coefficients are to dropping different disability groups. Outcomes are a binary indicator of whether a student withdrew in the middle of the semester and current semester GPA. We regress outcomes on whether a student was approved for accommodations as described in equation 2.

Figure A8. Short-Term Impacts (Dropping Disability Groups)



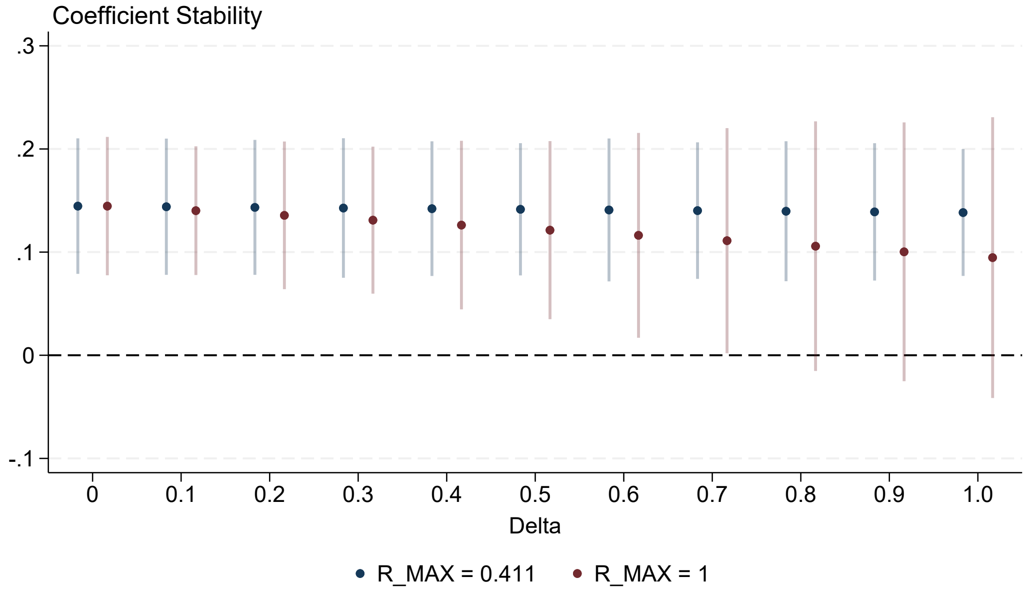
(a) Current Semester GPA



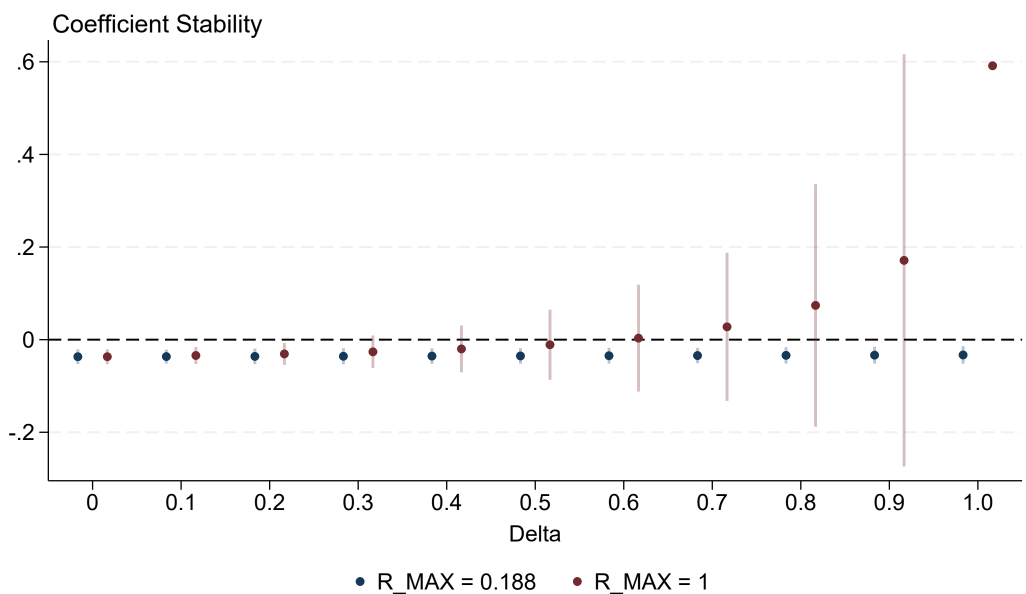
(b) Withdraw From Semester

Notes: This figure shows how sensitive treatment effect coefficients are to unobservables using the method described in Oster (2019). Delta is the relative importance of unobservables and observables at predicting selection into treatment (e.g., delta = 0.5 implies unobservables are 50% as predictive of selection into treatment as observables). We present results where we allow the maximum R^2 to be 1 and 1.3 times the regression described in equation 2. Confidence intervals are calculated via bootstrapping. We exclude CIs for when $R^2 = 1$ and $\delta = 1$ for presentation purposes. See equation 2 for details on outcomes and controls.

Figure A9. Coefficient Stability Using Oster (2019) Approach



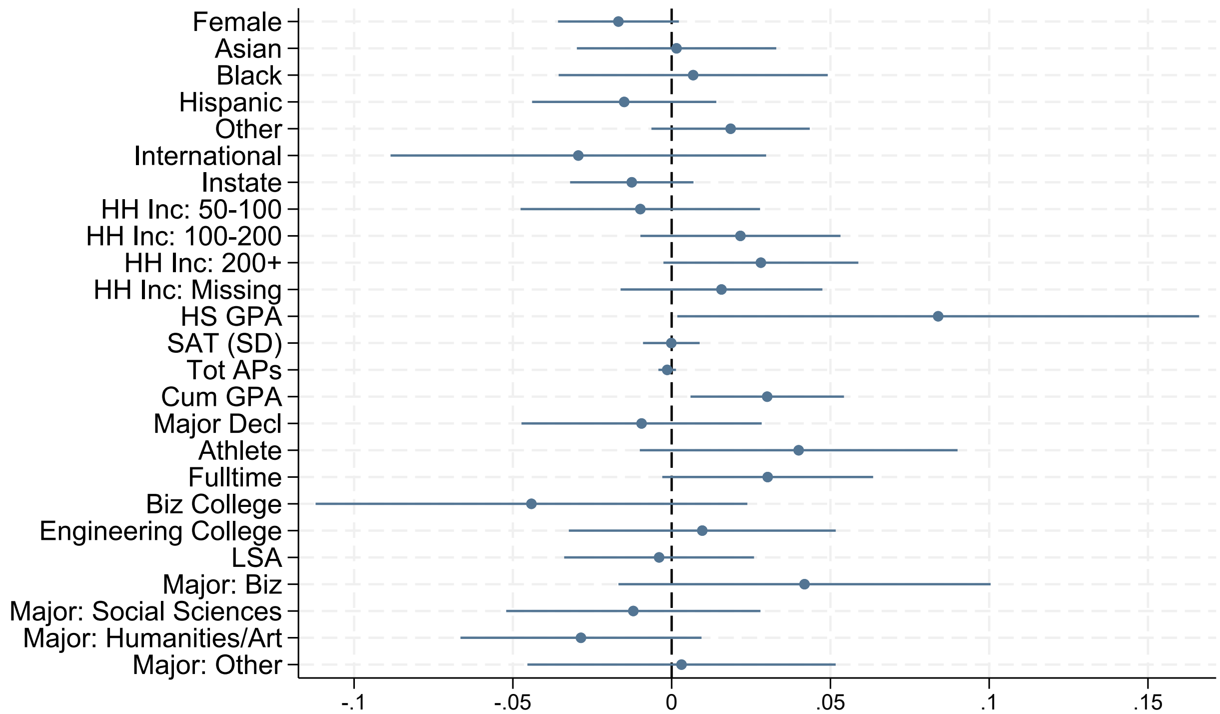
(a) Current Semester GPA



(b) Withdraw From Semester

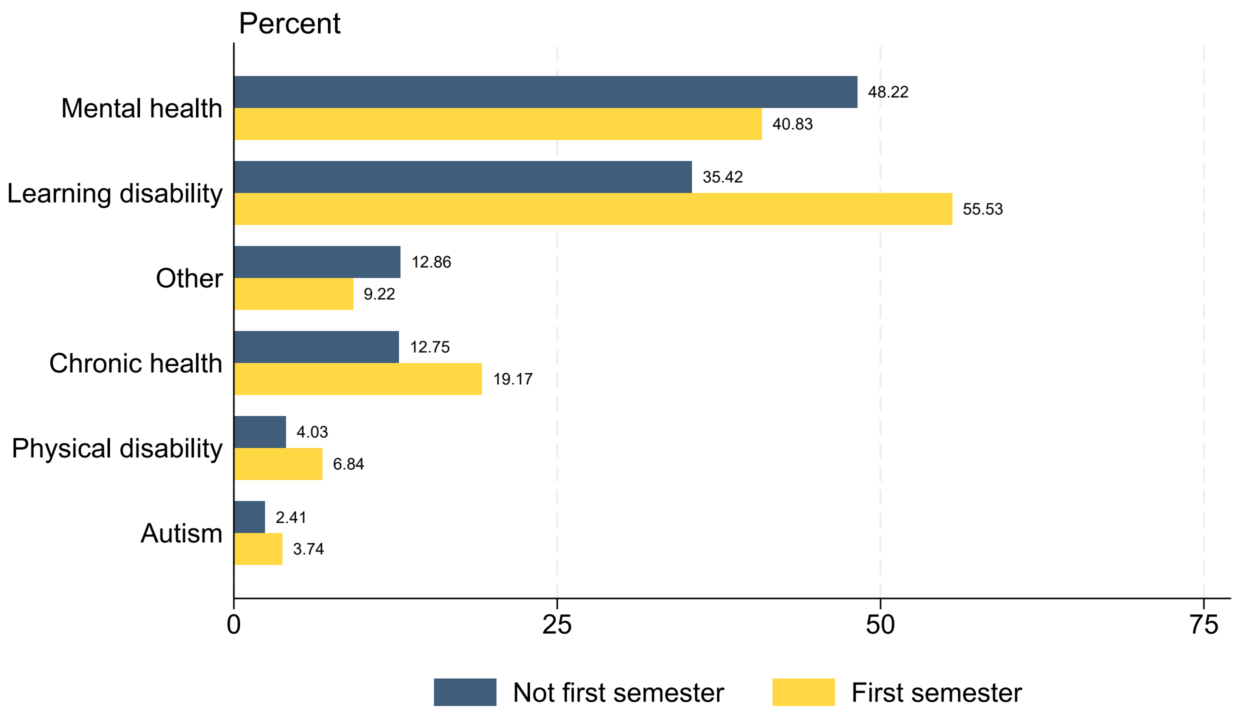
Notes: This figure shows how sensitive treatment effect coefficients are to unobservables using the method described in Oster (2019). Delta is the relative importance of unobservables and observables at predicting selection into treatment (e.g., delta = 0.5 implies unobservables are 50% as predictive of selection into treatment as observables). We present results where we allow the maximum R^2 to be 1 and 1.3 times the regression described in equation 2. This exercise includes the following extra control variables: prior documented disabilities (ever having an IEP or 504 plan), standardized test scores (grades 8 and 11), attendance, disciplinary records (suspensions and expulsions), measures of economic disadvantage and, and high school characteristics (demographics, average test scores, and urbanicity). Confidence intervals are calculated via bootstrapping. We exclude CIs for when $R^2 = 1$ and $\delta = 1$ for presentation purposes. See equation 2 for details on outcomes and controls.

Figure A10. Coefficient Stability Using Oster (2019) Approach Among In-State



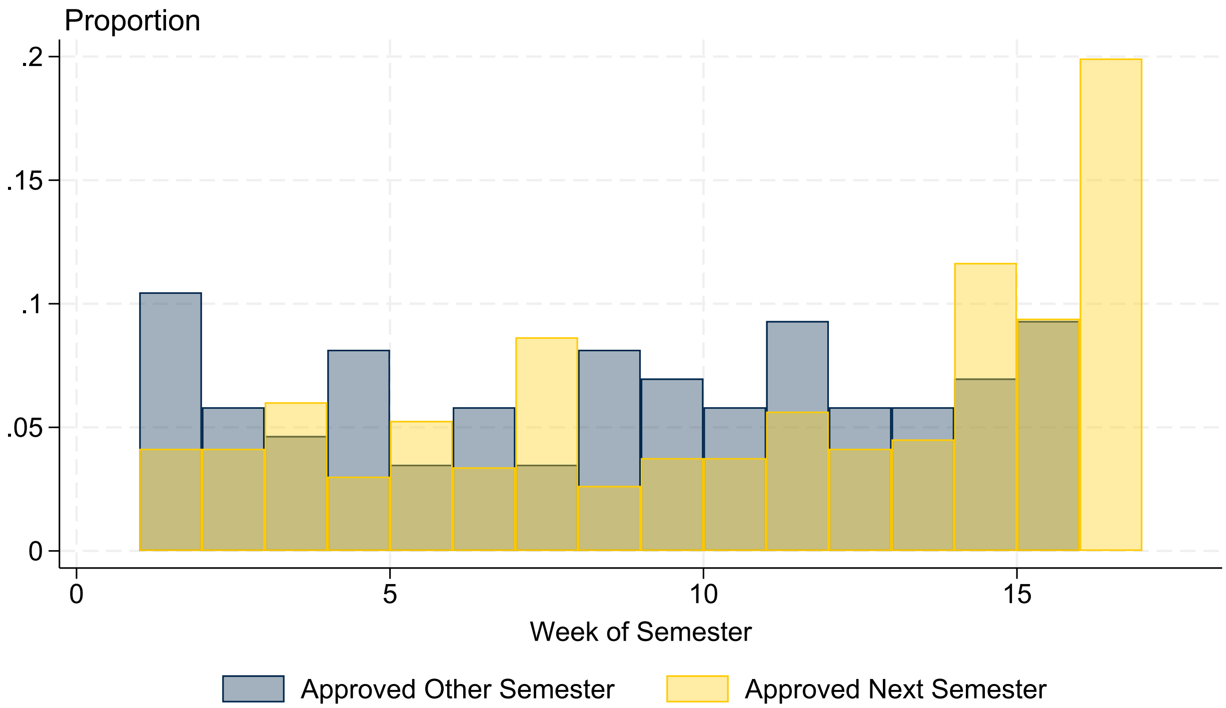
Notes: This figure presents point estimates from a regression, where the outcome is 1 if a student was approved for accommodations in the semester they applied and 0 if the student was approved in the semester after they applied. It also includes college entry cohort x semester of application FE, week of semester of application FE, and a binary indicator for if this was a student's first semester in college. All independent college variables are from the semester prior to application. For students applying in their first semester of college, we set these variables to zero and include an indicator for a student's first semester. Robust standard errors are used.

Figure A11. Predicting Approval Probability Among Applicants (Compared to Students Approved in Next Semester)



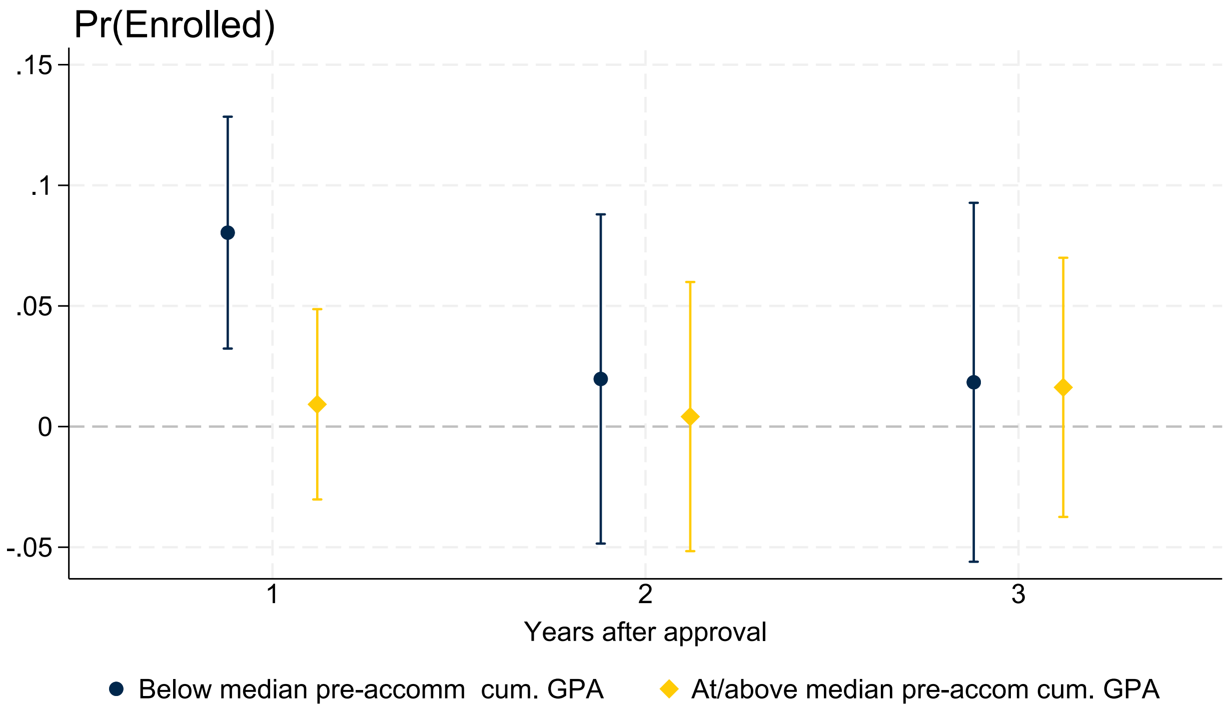
Notes: This figure shows the the type of disability a student is reported as having based on when they are approved (first semester in college vs other semester) for students enrolled in Fall 2021-Winter 2025.

Figure A12. Disability Approved for By Semester in College They Are Approved



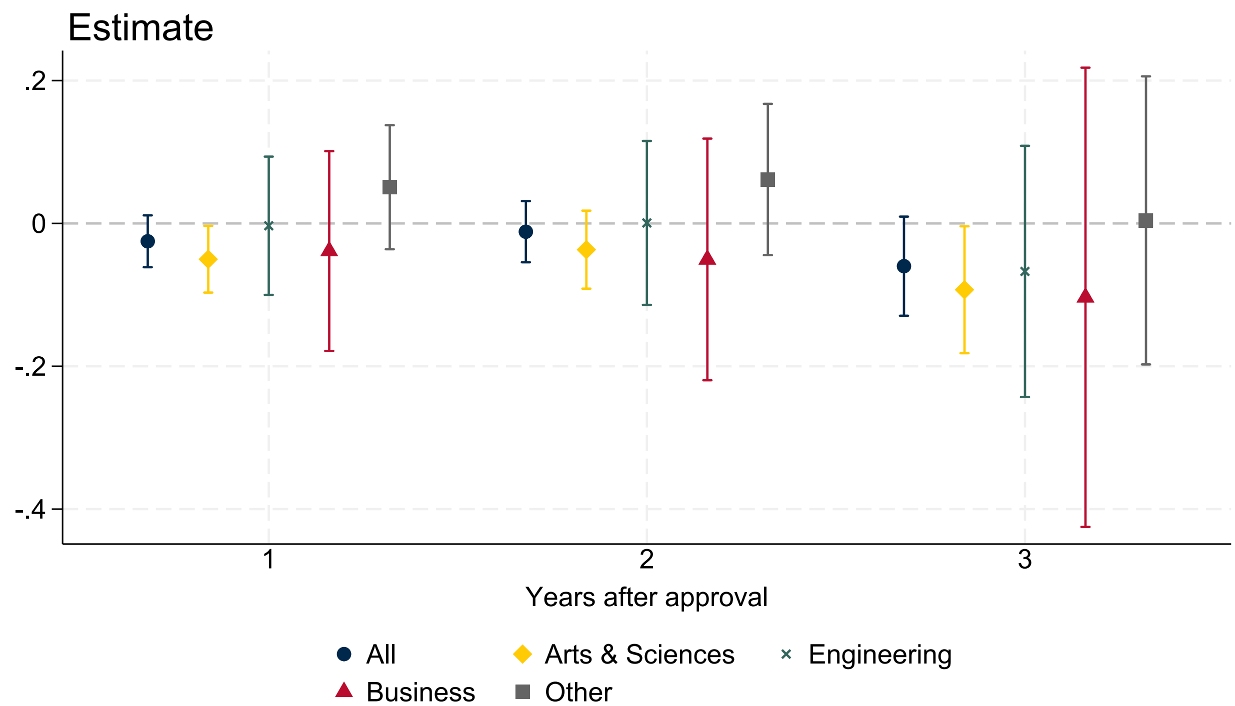
Notes: This figure shows when in the semester students requested a meeting with the disability office among students who were approved in a semester different from the one they applied.

Figure A13. Week of Semester of Meeting Request Among Students Approved In A Semester Different From The One They Applied



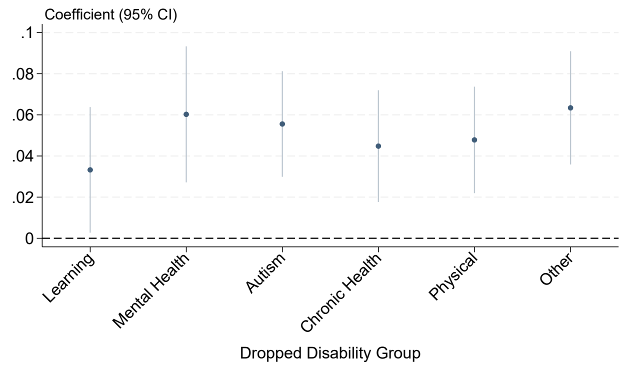
Notes: This figure plots coefficients from regressions, where we regress the probability a student is enrolled on an indicator for accommodations approval (see equation 2). Outcomes are evaluated at 1-, 2-, and 3-year horizons after the application semester. Regressions are run separately for students above and below median pre-accommodations application semester cumulative GPA (we exclude first-semester applicants). Error bars show 95% confidence intervals.

Figure A14. Effect of Accommodations on Persistence by Lagged Cumulative GPA

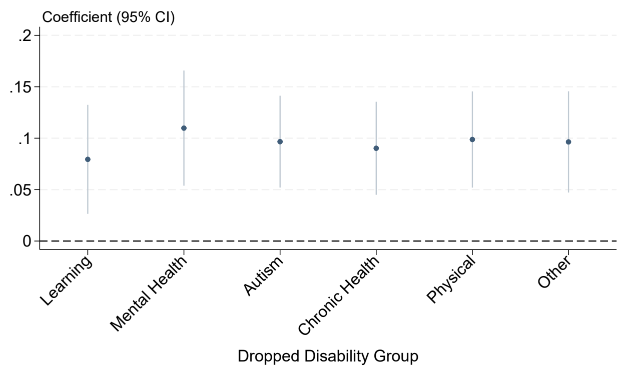


Notes: This figure plots coefficients from regressions of the student–semester course-bundle GPA on an indicator for accommodations approval (see equation 2). Outcomes are evaluated at 1-, 2-, and 3-year horizons after the application semester. To construct the course-bundle GPA, for each student–course we first compute the course's mean GPA in that term excluding the focal student's grade, then average these values across the courses a student takes in a semester; for each horizon, we average this measure across all semesters within the window after application. Error bars show 95% confidence intervals.

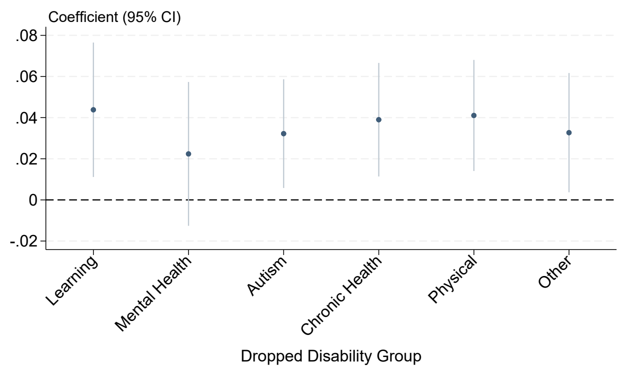
Figure A15. Effect of Accommodations on Course Difficulty One, Two, and Three Years After Approval



(a) Enrolled in Semester



(b) Semester GPA (Avg)



(c) Major in STEM

Notes: This figure shows how sensitive treatment effect coefficients are to dropping different disability groups. Outcomes include whether a student is enrolled the following year, the average GPA over the following year (excluding the semester of application), and whether a student declared a STEM major. Outcomes are regressed on whether a student was approved for accommodations. See equation 2.

Figure A16. Long-Run (One Year) Impacts (Dropping Disability Groups)

Appendix B. Decomposition Exercise

In addition to, for example, documenting trends in accommodations use, we wish to decompose growth into observable and unobservable factors. We do this using a standard Oaxaca-Blinder Decomposition (Blinder, 1973; Oaxaca, 1973). This approach breaks down the difference in average outcomes between two groups into parts that are "explained" by observable differences in characteristics and parts that are "unexplained" due to differences in how those characteristics relate to the outcome. Although not a causal method, it offers a useful accounting exercise to quantify which factors are most associated with changes in usage over time.

This is best illustrated through an example. Suppose we want to understand how much of the increase in accommodations use between Fall 2011 and Fall 2021 cohorts is due to changes in student characteristics. Let:

- Y_{2011}: mean probability of ever using accommodations in the Fall 2011 cohort
- Y_{2021}: mean probability of ever using accommodations in the Fall 2021 cohort
- X_{2011}, X_{2021}: mean vector of observed characteristics for each cohort
- $\beta_{2011}, \beta_{2021}$: estimated coefficients from regressing Y on X within each cohort

We begin by estimating the following linear probability models separately for the 2011 and 2021 cohorts:

$$Y_{2011} = X_{2011}\beta_{2011} + \epsilon_{2011}$$

$$Y_{2021} = X_{2021}\beta_{2021} + \epsilon_{2021}$$

The observed difference in accommodations usage between the two cohorts is:[43]

$$\Delta = Y_{2021} - Y_{2011} = X_{2021}\beta_{2021} - X_{2011}\beta_{2011}$$

[43] Assuming exogeneity, the errors are mean zero and cancel out.

We can rewrite this difference by adding and subtracting $X_{2021}\beta_{2011}$:

$$\Delta = \underbrace{(X_{2021} - X_{2011})\beta_{2011}}_{\text{Explained}} + \underbrace{X_{2021}(\beta_{2021} - \beta_{2011})}_{\text{Unexplained}}$$

The explained component tells us how much of the growth in accommodations usage can be attributed to differences in student characteristics between the 2011 and 2021 cohorts, holding the relationship between those characteristics and accommodations fixed at the 2011 level. The unexplained component captures how much of the difference is due to changes in the relationship between characteristics and accommodations usage over time (e.g., if having an IEP became more predictive of usage or if processes changed inside the disability office).

This decomposition allows us to quantify how much of the increase in accommodations usage is associated with compositional changes (e.g., rising prevalence of K-12 disability identification or changes in student demographics) and how much is driven by shifts in institutional behavior, policy, or other unobserved factors.

In addition to measuring the effect of total compositional change, we want to estimate the effect of changing particular characteristics. This means generating the distribution for a particular characteristic from the Fall 2011 cohort in the Fall 2021 sample, while holding all other variables constant. This allows us to answer, for example, how much did changes in 504 rates in K-12 contribute to changes in accommodations rates in college? To do this, we simply take the mean change in observable characteristics across the two cohorts and multiply it by the estimated effect of the observable characteristic.