Do Transfer Students Harm Direct Admits? A Peer Effects Case Study

James Lee*

Click here for the latest version

This version: October 30, 2025

Abstract

In recent years, policymakers across the United States have established more programs to help community college students transfer to four-year programs to earn bachelor's degrees. Evidence from recent papers (Bianchi, 2020, Genakos and Kyrkopoulou, 2023, Machado et al., 2025) suggests that the implementation of similar programs to expand educational access to non-traditional students may have detrimental effects on traditional students. By using administrative and post-graduation survey data from one of the University of California schools, this paper is the first to investigate the peer effects of community college transfer students on students who are admitted through traditional channels (direct admits). To identify these effects, I compare students with similar academic preparation and course preferences who are exposed to different shares of transfer students in their courses due to randomness in the scheduling of courses. In the short run I find a small, statistically significant positive effect of transfer exposure on direct admits' grades that is visible in upper and lower division courses and for all fields of study. These effects appear to be driven by a "curve effect": because transfer students academically perform worse on average, they increase the ranking of direct admits. Controlling for the major choice of direct admits (which is minimally impacted by transfer exposure), I find that direct admits who are more exposed to transfer students in their college career graduate faster. I do not find statistically significant effects on labor market outcomes, though the estimates are noisy.

*I am extremely grateful for guidance from my advisor Adriana Lleras-Muney and my committee members Kathleen McGarry, Robert Fairlie, and Yotam Shem-Tov. I would like to thank the Student Affairs Information and Research Office, the Registrar, the Admissions Office, and the Academic Planning and Budget Office for their help with providing the data used in this report. I would also like to thank the Transfer Student Center for their support of this project.

1 Introduction

Community colleges have emerged as a promising pathway to increase the education and upward economic mobility of students from disadvantaged backgrounds. In recent years, there has been a push across the United States to encourage transferring from community colleges to four-year universities. In 2024, Illinois passed a law to guarantee admission for Illinois community college students to the University of Illinois schools (Tasleem, 2024). Starting in 2006-2007, Virginia public four-year institutions also began developing their own transfer admission guarantees (Shi, 2023). California, in particular, heavily emphasizes the transfer pathway for its students. With 116 community colleges serving on average 2 million students every year, California has several programs to encourage transferring to the California State University (CSU) and University of California (UC) systems, such as the Associate Degree for Transfer to guarantee admission to a CSU, or the Transfer Admission Guarantee to guarantee admission to certain UCs. Despite the large presence of transfer students already, government officials still advocate for more students to attain a postsecondary degree or certificate through the transfer system (Echelman, 2024).

However, there is an going debate about not only how to reform or implement transfer policies, but whether to do so at all. There is evidence that transfer students may not benefit as much as expected from transferring - the marginally accepted transfer student may actually face worse long-term outcomes than the marginally rejected transfer student (Miller, 2025). The transfer pathway is also difficult to navigate, with students facing issues like stigma and a loss of support networks.[1] From a university perspective, admitting more transfer students means fewer spots for students who come directly from high school (direct admits), especially under capacity constraints.[2] With finite resources available, this means less funding and support for each student. As transfer students typically come from lower-

[1] In addition, it is worth noting that while 80% of community college students want to eventually earn a bachelor's degree, only 25-33% will transfer to a four-year program within 6 years and only 16% will manage to earn a bachelor's degree within 6 years (Velasco et al., 2024). The transfer system across most of the US is also confusing to navigate. Many students are unsure of the requirements to transfer to most schools, and there are not enough advisors for students at community colleges. As a result, transfer students on average lose 40% of the credits they previously earned once they transfer (Jenkins and Fink, 2016).

[2] As an example, the University of California - San Diego campus ended their community college transfer guarantee policy in 2014 due to the overwhelming number of students (The San Diego Union-Tribune, 2012).

income backgrounds, from a revenue perspective admitting more transfer students results in less money for the university. Finally, as transfer students come with a different background and type of preparation, it is not immediately clear how the presence of transfer students affects the direct admits who are already enrolled in the receiving university. Surprisingly, there is no evidence yet on how community college transfer students affect direct admits.

This is the first paper to address this issue by investigating whether the college experience and outcomes for direct admits is negatively impacted by the presence of transfers students. For direct admits, it is not immediately clear what effect transfer students may have on them. Transfer students typically enter as juniors/third-year students, and, depending on transferred credits, would only need to take major-required classes. If they are under-prepared, then admitting more transfer students is the same as admitting more lower-quality students. This could negatively impact direct admits by slowing down the class with their questions and causing direct admits to learn less. However, in competitive classes that curve grades, this could artificially boost the grades of direct admits. Transfer students could also have a positive social effect as they are possibly more persistent upon entering than direct admits and possess other qualities like more maturity and a different life perspective (Thomas, 2025).

This paper uses administrative panel data from the Admissions Office and the Registrar at one of the University of California schools, as well as survey data collected by the Student Affairs and Information Research Office (SAIRO), to study the peer effect of transfer students on direct admits in terms of their class grades, graduation likelihoods, major choices, time to degree, and immediate post-graduation outcomes. I also conduct in-depth interviews and focus groups with 40 students to understand the relationship between transfer students and direct admits inside and outside of class in order to gather opinions from each group and their own experience at university.

The main concern in assessing the effect of transfer students on direct admits is that exposure to transfer students may be correlated with other factors that affect outcomes. For example, transfer students often choose lower paying majors. As a result, direct admits who choose these majors will be observed to have lower incomes at graduation and higher exposure to transfer students. My identification strategy then relies on a conditional exogeneity assumption: I control for all the predetermined characteristics that determine the level of preparation of direct admits and I control for their initial choice of major. To rule out further confounding on observables (for example, two equally prepared STEM students might choose different courses and this preference might be correlated with the share of transfer), I leverage information I obtained from interviews regarding how students choose their courses. This choice depends primarily on the professor and time and day that courses are offered. I assume and show evidence that conditional on preparation and course factors, exposure to transfer students is as good as random.[3] This strategy I use for identification is similar to the strategy used in Fischer (2017).

This allows me to find a small but statistically significantly positive causal effect. This effect does not vary whether the class is a lower-division introductory class or a more advanced upper-division class, only varies slightly by discipline (e.g. STEM, social sciences, humanities), and is in line with the estimates found in other peer effects in higher education papers (e.g. Feld and Zölitz (2017) finds a one standard deviation increase in average peer GPA causes a 1.26% of a standard deviation increase in student grades). While this effect is positive, it does not explain whether the peer effect is indeed causal or a mechanical result from class curving.

To investigate further, I consider cumulative exposure to transfer students over time. The empirical strategy I use for the estimation of contemporaneous effects can be adapted to estimate long-run cumulative effects. However, this requires controlling for a very large set of controls which is computationally burdensome.[4] Therefore, I adopt a modified strategy that relies on controlling for summary measures of academic histories. Considering lagged exposure on class grades, I find a negative effect on grades, suggesting that the previous positive effect is simply due to class curving, as students who have taken classes with more transfer students do worse. Nevertheless, taking classes with transfer students increases retention in initial major choice by a small amount, likely due to the curve effect allowing

[3]Other class composition/peer effects in education papers, such as Hoxby (2000), use variation across cohorts to identify effects. Based on the construction of my dataset, I can only fully observe 3 cohorts of students, so I currently do not have enough variation to use this strategy.

[4]Adapting the strategy would require keep track of each students' academic history, such as courses taken and professors. This leads to thousands of control variables, which is possible to set up but not computation feasible to use in a regression. Future work includes using the machine learning methods in Chernozhukov et al. (2017) to reduce the dimensionality of the controls.

direct admits to have high enough grades to not be forced out of their major.

I end by investigating how overall cumulative exposure to transfer students affects final academic performance (time to graduation, GPA) and initial labor market outcomes. I find that students exposed to more transfer students are more likely to graduate sooner, which is consistent with the evidence on initial major retention. Due to sorting away from STEM by less prepared direct admits however, transfer exposure may initially show negative effects on labor market outcomes, since STEM has lower transfer shares and better employment outcomes. To address this, I condition on final major (which transfer students only have a small effect on and is thus not a significant mechanism) to focus on the effect of exposure to transfer students and do not find statistically significant effects on employment and incomes, though the standard errors are large.

This project relates heavily to the large literature that studies peer effects in education settings, namely how the characteristics and behaviors of peers in the classroom affect students performance. Many studies have investigated peer effects in college, such as from classmates (Carrell et al., 2009, Booij et al., 2017, Feld and Zölitz, 2017, Golsteyn et al., 2021, Fairlie et al., 2024), by gender (Oosterbeek and van Ewijk, 2014, Fischer, 2017, Feld and Zölitz, 2022), from roommates (Sacerdote, 2001, Zimmerman, 2003, Stinebrickner and Stinebrickner, 2006), from high school peers (Fletcher and Tienda, 2008), and effects on job preferences (Marmaros and Sacerdote, 2002, Arcidiacono et al., 2016, Jones and Kofoed, 2020) or behavior (Wilson, 2007, Carrell et al., 2008, DeSimone, 2009).[5] I contribute to this literature by being the first paper to analyze peer effects from community college transfer students on direct admits, a key issue in the policy debate. I also consider not only the effects on grades but also on later academic performance and post-graduation outcomes.

Most related to this study are two papers that have considered the peer effects of transfer students - specifically on each other. Ehrenberg and Smith (2004) uses grouped data from the State University of New York and finds that transfer students have higher graduation rates when attending campuses with larger shares of transfer students. Nutting (2005) directly follows up on their study using individual-level data and finds the opposite - specifically that

[5] Sacerdote, 2011 and Barrios-Fernandez, 2023 provide in-depth reviews of the peer effects in education literature.

transfer students have lower graduation rates in departments with a larger share of transfer students.[6] My paper differs in that I consider the peer effects of transfer students on direct admits instead.

This paper also contributes to the literature about community college transfer students. Many studies have considered how transfer students perform once they have transferred, both academically and socially. Transfer students often lose credits after transferring, experience a phenomenon known as "transfer shock" where their GPA drops immediately after transferring, have a hard time adjusting to their new school, and face lower on-time graduation rates. Hills (1965) is one of the first to describe the transfer shock phenomenon, which most of the literature finds evidence of (Monaghan and Attewell, 2015, Lakin and Elliott, 2016, Elliott and Lakin, 2021, Transfer Opportunity Project, 2022, Jaggars et al., 2023). Other studies, like Flaga (2006), Townsend (2008) and Cepeda et al. (2021), focus on the qualitative experience of the adjustment process for transfer students, like adapting to the new campus and its resources and losing their previous support network. Other studies have analyzed different transfer policies and the positive effects on degree completion or labor market outcomes (Baker, 2016, Baker et al., 2023, Shi, 2023), though Miller (2025) finds that the marginally accepted transfer student may actually face negative returns in the long-run when compared to the marginally rejected transfer student. Similarly, Shirley et al. (2023) finds that transferring may extend time to degree by one semester and result in increased student loan debt.

While about transfer students, this paper focuses on the spillover effects of admitting more transfer students on direct admits. My setting also differs from many papers, as there is a larger presence of transfer students at the UC campuses compared to other schools. Thus, I contribute to this literature by providing new qualitative interview data describing how transfer students and direct admits interact both in class and outside of class, and how

[6] In a different setting, Genakos and Kyrkopoulou (2023) considers a transfer student policy change in Greece where students from large, poor families could transfer to a university closer to their home if they were originally allocated to a different university. This led to a large number of lower academic quality students transferring to a top university. Transfer students in their context, however, are different from transfer students in this paper's context as they are known to be lower in academic quality based on their entrance exams and original allocation, transferring laterally, and transferring before they even begin college. Similarly, Bianchi (2020) studies a policy change in Italy that increased access to education by allowing less academically prepared students to enroll in university. Their paper is not about transfer students.

each views the other group, as well as quantitative evidence of peer effects from transfer students on direct admits.

The remainder of this paper is as follows. Section 2 describes the linked administrative data and interviews and focus groups conducted. Section 3 lays out a conceptual framework to provide context for the empirical results. Section 4 presents the empirical approach and results for the contemporaneous effects of taking classes with transfer students. Section 5 presents the empirical approach and results for the effect of cumulative exposure to transfer students on intermediate outcomes. Section 6 presents the empirical approach and results for the effect of cumulative exposure to transfer students on final outcomes. Section 7 concludes.

2 Data and Institutional Background

2.1 Institutional Background

The California higher education system was established with transfer students in mind. In 1960, the UC Regents and then-governor Pat Brown set up the California Master Plan for Higher Education. The Master Plan designated the University of California system for the top one-eighth of graduating high school seniors and for conducting research, the California State University system for the top one-third, and the community college system for any student who could benefit from additional instruction - whether it be vocational for job training purposes or academic for students to eventually transfer to a bachelor's degree program. The Master Plan also established a policy target of enrolling one new California community-college transfer for every two new California freshmen.

With 116 community colleges enrolling 1.8 million students today, making it the fourth largest university system in the world, the community college and transfer system in California is arguably one of the most robust in the United States.[7] The transfer process has gone through several changes since the 1960s. Individual UC campuses began Transfer Admission guarantee programs with specific community colleges in the 1980s before agreeing to make them with all community colleges in 2009. In 2010 the Associate's Degree for Transfer was

[7]The largest college systems are Indira Gandhi National Open University, National University, in Bangladesh, and Anadolu University, in Turkey.

created, which guarantees admission to any CSU school. California community college students can also use the ASSIST website to better prepare to transfer to a UC. Today, 29% of UC graduates and 51% of CSU graduates started at a California community college ("Key Facts", n.d.).

There are several reasons why a student may choose to go to community college and then transfer to a UC. The cost of attending community college is much lower than attending a UC.[8] Students must transfer into a UC at the junior level, so by attending a community college first they would only need to pay for two years of tuition instead of four years. Students may not be accepted into a UC directly after high school, but the acceptance rates for transfer students is slightly higher than the acceptance rate for direct admits - providing another benefit to transfer students. Some high school graduates may choose to go to community college and then reapply to a UC instead then. Some students may also go to community college as a second chance if they did not perform well in high school. There is also much less social stigma for going to community college in California versus many other states since the process is so integrated into the state's higher education system and so many students use the pathway.

After transferring to a UC, transfer students still face several issues on the path to graduation. Like transfer students elsewhere, they face a "transfer shock", which I confirm in my student interviews also occurs in my setting. This may be due to issues adjusting to the new school, navigating resources, transitioning from a semester schedule to a quarter schedule, and moving further away from home. In interviews with transfer students, they also experience negative stigma from certain student clubs - typically more competitive clubs that are career-oriented for business or pre-med students. Transfer students typically only have two years to finish their degree, so they must complete all their major requirements in a timely manner. In majors with sequences of classes, this results in a pattern where an incoming cohort of transfer students will take the same classes together. Transfer students are also barred from switching into certain majors after transferring. These majors are typically more competitive to enter, such as economics. Direct admits do not face as many

[8] For example, for Californian residents in 2025, average annual tuition is $1,390 at the California community colleges vs $14,934 at a UC.

restrictions. These students have four years to complete their degree and can switch into whatever major they want as long as they fulfill the requirements and can do so in a timely manner.

2.2 Admissions and Registrar Data

To investigate the possible peer effects of transfer students on direct admits, I use administrative data from the Admissions Office and Registrar of this particular UC campus. The Admissions and Registrar data are a cohort-based panel for all students who entered this school between 2012 to 2019. The data includes demographics, application information (such as high school or community college, GPA, test scores for direct entrants, place of origin, family background, and financial aid status), and transcript information (such as classes taken, grades, declared majors, and graduation status). Students who did not graduate may have dropped out, may have temporarily taken leave, or transferred out.

Table 1 reports summary characteristics split by direct admits and transfer students. Transfer students are slightly more likely to be White instead of Asian, are more likely to be from California and are more likely to be foreign than direct admits. Fitting the narrative that transfer students more likely come from disadvantaged backgrounds, they are more likely to be first-generation college students and are more likely to receive Pell grants. Transfer students are older than direct entrants, which is expected since they enter as juniors, but the median age is roughly three years older instead of just two, suggesting transfer students are comprised not only of students that did their first two years in a CC but also of students that took time between HS and college or took more time than expected in CC.

Transfer students also come to college with far fewer AP credits.[9] In terms of field of study, transfer students are more likely than direct admits to enter majors in the social sciences and humanities. STEM fields are the second most popular field for transfer students, but the share of transfer students entering STEM is far lower than that for direct admits. This does not appear to be driven by admissions, as table A.3 shows, with aggregate, publicly

[9] Table (A.1) includes summary statistics for test scores and GPA at previous school. Test scores and high school GPA are only available for direct admits, while community college GPA is only available for transfer students. Overall, transfer students are less academically well prepared and come from more modest backgrounds then direct admits. Table A.2 displays the statistics from table 1 over time.

available statistics, that transfer students do indeed apply for social science majors more than for STEM majors.[10]

Table 1 also displays summary statistics for academic outcomes. The overall graduation rates are comparable. However, transfer students have a lower on-time graduation rate.[11] Indeed, relative to their expected program length, transfer students on average take a quarter longer to graduate than direct admits, which is similar to findings in Transfer Opportunity Project (2022) and Shirley et al. (2023). For students who do graduate, transfer students typically stay in their original major. Direct admits however are more likely to switch majors and, overall, appear to switch from STEM fields to the social sciences.

2.3 First Destination Survey Data

The First Destination Survey is an annual online survey administered by the school for undergraduates who have graduated or are about to graduate and asks about employment status, graduate school plans, and preparation for life after graduation.

Table 2 shows average responses by survey year and student type starting in 2016.[12] The response rates of the surveys range from around 20-30%. The vast majority of outcomes can generally be split into 5 exclusive categories: employed full-time, employed part-time, seeking work, enrolled in a graduate program, or planning to apply to a graduate program.

For most of the sample, compared to direct entrants, transfer students are less likely to find any sort of employment and are more likely to still be seeking employment. Transfer students are less likely than direct entrants to have full-time employment, and instead slightly more likely to find part-time employment. In regards to graduate school plans, when

[10] It does not seem likely that transfer students apply strategically to social sciences majors in order to switch into more competitive majors, like those in STEM, because of the restrictions on which majors transfer students are allowed to switch into and based on how correlated the percentages are for what field transfer students enter and graduate in (see table 1). It is possible that transfer students apply for these majors because they have a higher chance of being admitted.

[11] On-time graduation for transfer students is calculated assuming a transfer student should graduate within 2 years (6 regular academic quarters) of enrolling.

[12] Table A.4 displays respondent demographics after matching respondents to the available registrar data. I use data from the 2016 survey year and later as 2016 is the first year that direct admits in my sample are expected to graduate. See Table A.5 for responses by survey year. Regarding any concern about the response rates, Fosnacht et al. (2017) find, regarding college surveys, that estimates based on survey data remained reliable even with a 5%–10% response rate for surveys with a sample size of at least 500. This survey data is also only used for two of the outcomes I analyze - the rest of my data is administrative.

Table 1: Summary Statistics for Direct Admits and Transfer Students

	Direct Admits	Transfer Students
Female	0.59	0.54
White	0.25	0.30
Black	0.05	0.04
Asian	0.34	0.25
Hispanic	0.20	0.21
Foreign	0.12	0.15
From California	0.73	0.91
First Generation College	0.19	0.28
First Generation Bachelor's	0.29	0.47
Pell Grant Recipient	0.34	0.50
Median Age	18.4	21.3
AP Credit Units	29.7	5.9
	(21.3)	(11.3)
Entered Arts	0.04	0.02
Entered Humanities	0.06	0.20
Entered Social Sciences	0.28	0.51
Entered STEM	0.62	0.26
Units Taken	179	92
	(36)	(21)
Courses Taken	43.1	22.6
	(9.8)	(5.5)
Did Not Graduate	0.07	0.06
Graduated in Arts	0.04	0.02
Graduated in Humanities	0.05	0.19
Graduated in Social Sciences	0.33	0.48
Graduated in STEM	0.50	0.24
On-Time Graduation Rate	0.73	0.55
Time to Degree (Years)	4.05	2.30
	(0.51)	(0.65)
GPA at Graduation	3.43	3.35
	(0.46)	(0.49)
Double Major	0.09	0.03
Has Minor(s)	0.02	0.00
Switched Major	0.56	0.23
Switched Department	0.50	0.12
Switched Discipline	0.20	0.05
Cohort Size	5939	3186

Notes: "Did Not Graduate" is calculated as the percentage of the cohort that were not observed to have graduated by June 2024 and can be students that dropped out of college or transferred out. Standard deviations are reported in parentheses.

Table 2: First Destination Survey Results for Direct Admits vs. Transfer Students

	Direct Admits	Transfer Students
Employed	0.48	0.39
Full-Time	0.42	0.30
Part-Time	0.06	0.09
Seeking Employment	0.21	0.29
Enrolled in Grad School	0.18	0.13
Planning for Grad School	0.11	0.16
Other	0.02	0.03
Average Income	55,590	42,699
	(32,955)	(32,207)
Internships	1.72	0.93
	(1.43)	(1.55)
Response Rate	0.29	0.21
Total Number of Responses	7,886	3,281

Notes: Results above are calculated for survey years 2016-2020 after adjusting for nonresponse bias to survey using inverse propensity weights. Income is reported in 2016 dollars and winsorized at the 1st and 99th percentile. Standard deviations are reported in parentheses. "Other" includes options such as joining the military and choosing to do nothing. Response rates are calculated as the number of responses divided by the number of students that graduated in the calendar years 2016-2020.

compared to direct entrants, transfer students are less likely to be in graduate school and more likely still planning for graduate school.

Any student who answers that they have found employment is then asked how much their income will be for the next 12 months. Based on reported income, employed transfer students make \$5,000 to \$22,000 less than employed direct entrants (in 2016 dollars). This is potentially due to slightly more of the employed transfer students being in part-time jobs as opposed to full-time jobs.

The internships row reports the average number of internships while enrolled. Direct entrants complete roughly 0.6 to 0.9 more internships than transfer students. This may explain why direct entrants are more likely to find full-time employment with higher wages. Transfer students are at the university for a shorter amount of time than direct admits however, so it is possibly expected that transfer students complete roughly one less internship.

2.4 Interview and Focus Group Results

I also conduct individual interviews and focus groups with 40 current students to understand how transfer students and direct admits interact. Appendix B lists the questions in detail.

The questions differ between the two student groups. For transfer students, I focus on understanding their experience before and after transferring, as well as their experience interacting with direct admits, prejudice they face, and what advantages they have over direct admits. For direct admits, I focus on their experience in school, as well as their thoughts about different student groups that are similar to transfer students, their experience interacting with transfer students, and how they navigate the university. From these interviews, I learned several important aspects about how these student groups interacted and chose classes. I use these results to inform my identification strategy as well as my empirical results and discuss them later in the paper as they become relevant.

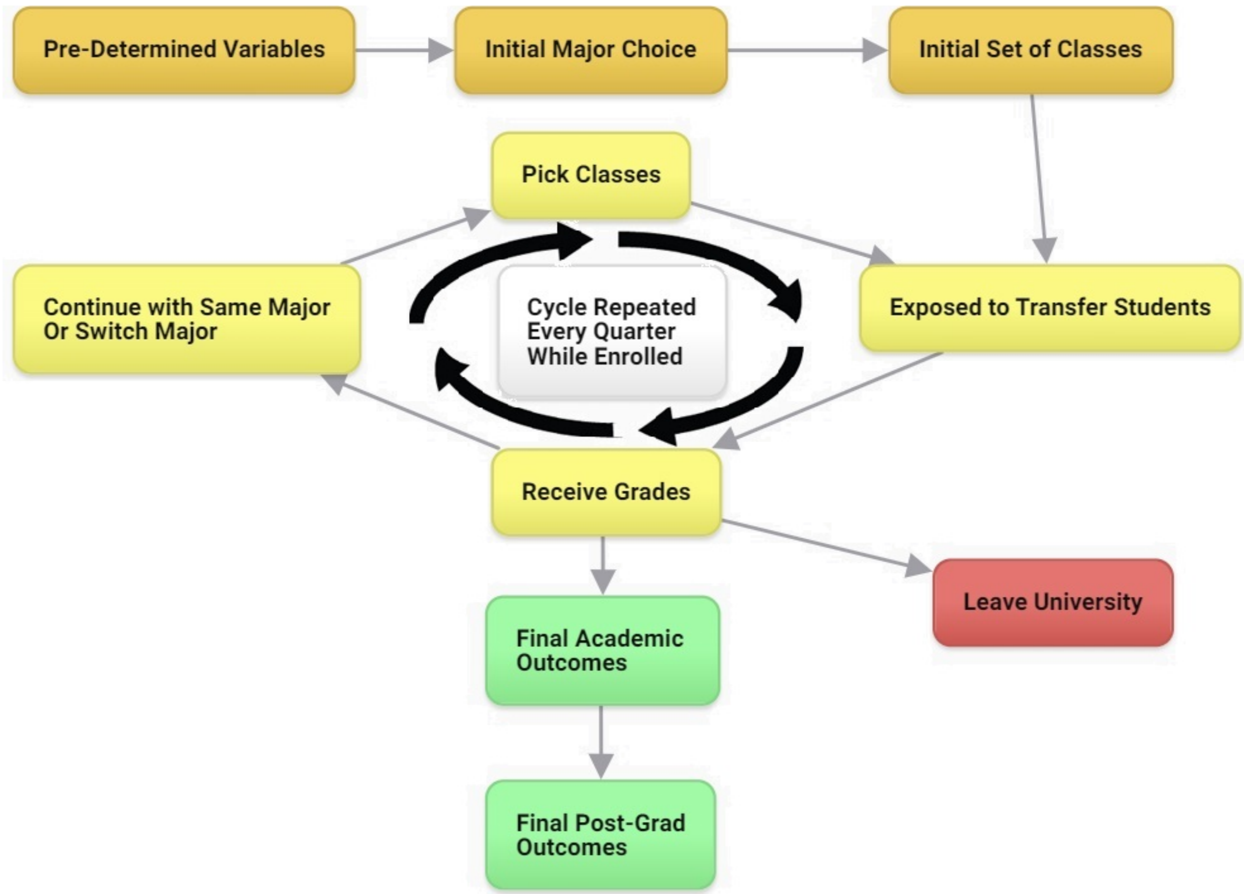
3 Conceptual Framework

In this section, I provide a brief conceptual framework laying out the general timeline of how student decisions and outcomes are made in college and immediately afterwards. I focus on the case for a direct admit who has already decided to enroll in the university. Figure 1 visualizes the stages I describe below.

Before arriving to college, students have already acquired many traits and skills that affect their choice of college and once they arrive in college their choice of major and courses. These predetermined characteristics, which include their demographics, high school GPA, test scores, and AP credits, also potentially impact their final outcomes. Different majors will attract different students based on both the field (e.g. STEM vs humanities) and how competitive the major is. For example, there are far fewer direct admits starting in majors like Nordic Studies or Greek than Psychobiology (the most popular choice for pre-medical students) and Economics. Conditional on a given entry major, students with more AP credits are more likely to start in more advanced classes, simply because they have passed out of the more introductory classes like algebra. Students who scored higher on the SAT or ACT or have higher high school GPAs should also perform better in their classes.

Second, once a student starts school, they face a repeated set of decisions every quarter. Given their major at entry, a student will choose a set of classes (typically 3 to 4) to take. It is in these classes where students may potentially be exposed to few or many transfer

Figure 1: Diagram of Choices Made Before, During, and After College



Notes: The figure above visualizes the stages described in this section for the conceptual framework behind direct admits making choices in college and subsequently getting exposed to transfer students before their final outcomes are realized.

students. After taking the class, the student will receive a grade and then decide what to do. They can either leave the school (either dropping out of college or transferring out), switch majors, or keep the same major. If the student chooses to leave, then they exit the data and they are never observed again. Students who stay may switch majors because they find out that they are interested in another subject or because they have failed to meet the requirements of their current major. In either case, it is the choice of major that then influences what classes to take next. They will then repeat this cycle again.

When direct admits take classes with few or many transfer students, it is not immediately clear what the effect will be. There could be negative effects, for instance if transfer students slow the class down by asking many questions as mentioned by one interviewed student. Professors may teach the content slower, thus causing students to be less prepared for future classes. Overall however, the interviewed direct admits did not personally have any evidence of the negative stereotypes of transfer students or personally believe them.

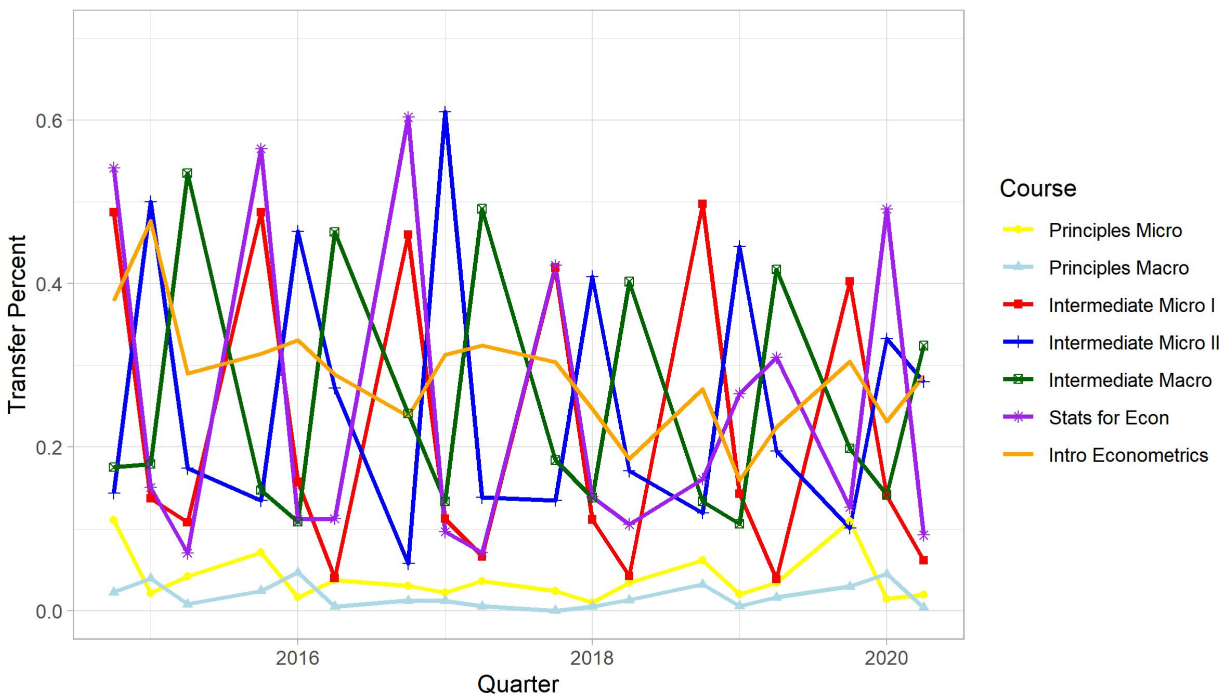
There could also be a positive effect if transfer students act as positive role models, as many interviewed direct admits thought of transfer students as being driven, resilient, hard-working and more mature - Golsteyn et al. (2021) finds that students perform better in the presence of persistent peers.[13] Based on the interviews however, it is also possible that this channel isn't very powerful as it doesn't appear that transfer students and direct admits interact much in class - when asked, many transfer students felt that direct admits thought negatively about them. Despite not having any personal experience of prejudice by their direct admit classmates, most of the transfer students interviewed only made friends with other transfer students. They also found it hard to make friends with direct admits since most direct admits typically already had established friend groups. Most transfer students did not interact with direct admits in their classes, but made friends outside of class in extracurricular activities like intramural sports or non-competitive student clubs.

There could be a positive effect because of class curving. If transfer students generally perform worse than their direct admit counterpart, then they "help the curve" by bringing down the average. Direct admits may receive better grades for the same performance if their class has more transfer students. While this would be a benefit for direct admits, their grade would simply be slightly inflated and there would not be any lasting benefit in terms of learning. However, having higher grades comes with benefits, such as for satisfying major requirements which then helps direct admits stay in their initial major of choice.

Based on the statistics in table 1, students who major in humanities or social sciences are more likely to be exposed to transfer students than those who major in STEM. Within a given major however, students can vary with how many transfer students they are exposed to. For example, figure 2 plots the percent transfer students for required economics major classes over time. Every fall, the incoming cohort of transfer students in economics must

[13] One interviewed direct admit said that her roommate only dates transfer student men because they are more mature.

Figure 2: Percentage of Econ Major Classes that are Transfer Students Over Time



Notes: Each colored line plots the percentage of transfer students over time for a given required economics major class. The bottom two lines are for introductory economics classes that transfer students are supposed to have taken before transferring for the major.

take intermediate microeconomic theory I, hence a spike every year corresponding to the fall quarter for that class. Afterwards, they must take intermediate microeconomic theory II, followed by macroeconomic theory. As a result, a large percentage of students in this sequence can be made of transfer students depending on the timing. As direct admits can choose whenever they want to start or pause a sequence, there is variation in the percentage transfer students that a direct admit will take a class with.

Conditional on major, I expect students with higher pre-college measures of academic ability (test scores and high school GPA) to perform better in their classes and also stay within their original major. While these students may choose to switch majors because of their personal interests, they should be less likely to perform poorly in class and thus be “kicked out” of their major. For students who are forced to switch majors and choose not to leave the university, it is more likely that they switch into the humanities or social sciences. This is due to certain majors, like sociology, having a lower barrier to entry and requiring less classes to complete the major. As a result, I expect students with lower pre-college measures of academic ability to be exposed to more transfer students over time, as the humanities and social sciences have higher shares of transfer students than STEM.

In a separate mechanism, I expect students who have more AP credits or are more ambitious to be exposed to more transfer students early on. This is because transfer students typically do not take any introductory classes as they should have taken them before transferring. While most direct admits start in introductory classes, it is possible that more qualified and ambitious students choose to enroll in more advanced classes from the very start, e.g. starting off in intermediate microeconomics instead of introductory microeconomics.

Finally, once students have passed enough classes, they will graduate. Upon graduation, there are several types of outcomes to consider. The first would be academic outcomes like final GPA, time to degree, and the final major. If transfer students generally help direct admits, even if it is simply a mechanical effect from class curving, then I expect a beneficial effect on time to degree and final major for direct admits, as they would be less likely to fail and retake classes for their major. There could also be a beneficial effect on final major, however if students are actually learning less then this effect is less clear.

Based on their major and personal interests, there are also post-graduation outcomes to consider, like finding employment and income. It is less clear what effect transfer students might have on these outcomes. Based on table 2, transfer students are more likely to still be looking for a job or be in part-time employment. If transfer students influence the decisions of direct admits, then I would expect a direct admit that has been more exposed to transfer students to be more likely unemployed or in a part-time job. In summary, the potential impact of transfers on direct admits is ex-ante ambiguous.

4 Contemporaneous Effects

4.1 Identification

$$\text{Grade}_{ict} = \beta \text{Transfer Percent}_{ct} + \epsilon_{ict} \tag{1}$$

To ground the discussion, I first consider equation 1. The goal is to identify β, the effect of transfer students on the grade for direct admit i in a given class c at time t by using the percentage of a class that is transfer students as the primary variable of interest. It is possible that the percentage of transfer students is correlated with the error term ϵ_{ict}, for instance if students selected into classes specifically because of the presence of transfer students or for other reasons that are correlated with their presence.

To causally identify this effect, I leverage the rich administrative data and use a strategy motivated by the interviews with direct admits and how they choose classes once they have selected a major. Direct admits were very consistent in their rankings of the factors that determine how they choose classes: what classes they need to graduate with their major, whether the class is available, the reviews of the professor for the class at that time, and the day and time of the class. Transfer students were never mentioned in the rankings, and direct admits cannot predict when a certain class may have many transfer students or not. In fact, when asked if they could predict what type of student might be in a certain class at a certain point in the school year, the best guess direct admits came up with was whether there might be more STEM or humanities students based on the discipline of the class. The interviewed direct admits were unaware that transfer students take classes in waves, particularly in majors with sequences of classes. As such, I control for all the factors (which I will refer to as class selection controls) above to identify the peer effect of transfer students on direct admits' grades. Thus my identification assumption is that conditional on major and class selection controls, the share of transfer students that a direct admit is exposed to in a given course is as good as random.

Figures A.0a and A.0b provide motivating figures for this strategy by plotting the share of certain students characteristics over time for two intermediate classes - one in economics and one in psychology. Other characteristics of students do not fluctuate much over time, however, transfer percentage has a clear seasonal pattern that spikes every fall quarter. Table A.6 shows the result for checking the conditional exogeneity of transfer percentage. Once class selection controls are added, other observable characteristics of direct admits are not significantly correlated with transfer percentage of classes. I later show robustness checks and conduct an Oster (2017) robustness exercise as further validation.

4.2 Empirical Approach

I estimate the peer effect of transfer students on direct admits' grades in a given class according to the following equation:

$$\begin{aligned}\text{Grade}_{ict} =& \beta \text{Transfer Percent}_{ct} + \alpha \text{Professor}_{ct} + \gamma \text{Class Time}_{ct} \\ &+ \theta \text{Major}_{it} + \psi \text{Units}_{i,t-1} + \zeta_c + \phi_t + \epsilon_{ict}\end{aligned} \tag{2}$$

where Grade_{ict} is the grade (on the 4.0 grade point scale) for student i taking class c at time t. Professor_{ct} is the professor for the class at the time, and Class Time_{ct} is the time of day and days of the week the class meets. $\text{Units}_{i,t-1}$ is the lagged number of units a student has taken, as this determines the priority in which a student can enroll in classes.[14] ζ_c is a class fixed effect as different classes curve to different average grades, and ϕ_t is a time fixed effect to control for grade inflation. $\text{Transfer Percent}_{ct}$ is the percentage of the rest of the class that is transfer students. β is the main coefficient of interest in the model. If transfer students are indeed positive role models, or if there is an effect from class curving, then I expect β to be positive. If transfer students disrupt or slow down classes however, then I expect β to be negative since direct admits may learn less and thus perform worse.

To estimate the equation, I cut my sample to only include courses that took place between Fall 2015 and Spring 2020. As my data are defined by the entering cohort, I apply this sample selection to ensure that I observe the vast majority of undergraduate students on campus.[15] I also remove classes that have less than 10 students, as this is a campus with a large student population so there should not be any classes that meet with less than 10 students. Such classes are typically courses meant for research credit or thesis writing that do not actually meet. Figures A.2 and A.3 plot the distributions of transfer percentage at the class level, observation (direct admit-course) level and after residualizing by the class selection controls to show that there is still one-third of the original variation after including these controls.

[14] Outside of specific student groups like student athletes, seniors have the highest priority in enrollment, followed by juniors, etc. This ordering is determined in the registration system by the number of units a student has successfully completed up to that point. Within a given priority level, enrollment priority is randomly assigned.

[15] For example, if I were to include data from Fall 2014, there would potentially be students from the 2011 entering cohort who would still be taking classes as seniors, but they would not be in my administrative data. Calculating the percentage of transfer students in each class would then be overestimated.

Table 3: Contemporaneous Effect of Transfer Percentage on Grades

	Course Grade			
	(1)	(2)	(3)	(4)
Transfer Percent	0.308***	0.085***	0.082***	0.082***
	(0.020)	(0.020)	(0.020)	(0.019)
Class Selection Controls		Yes	Yes	Yes
Individual Characteristics			Yes	
Individual Fixed Effects				Yes
Average Outcome	3.401	3.401	3.400	3.400
	(0.799)	(0.799)	(0.803)	(0.803)
Observations	1,086,279	1,086,279	1,006,446	1,006,446
R^2	0.00	0.24	0.43	0.56

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in parentheses and clustered at the course-time level. The sample includes all grades of direct admits for classes that take place between Fall 2015 and Spring 2020. Transfer percent is measured from 0 to 1. Class selection controls is the full specification in equation 2. Individual characteristics include: ethnicity, age, gender, first generation status, Pell grant recipient status, origin, SAT and ACT test scores, AP credits, high school GPA, and lagged cumulative college GPA.

4.3 Results

Table 3 displays the results from estimating equation 2, with standard errors clustered at the course-time level. Column 1 includes no controls at all, and I find a positive impact of transfer percent on direct admits' grades. Column 2 shows the estimates from the main specification, and I find a smaller effect that is still positive and statistically significant. While the effect is small, it is not negative, so there does not appear to be any negative effect from transfer students. Columns 3 and 4 are robustness checks - in these specifications I control for individual demographics (column 3) and individual fixed effects (column 4). In both columns, the estimate itself does not change much. I also use the methods prescribed by Oster (2017), which is a sensitivity analysis technique to test the robustness of the estimated coefficient to potential omitted variable bias using how much the R^2 changes as an extensive set of observed controls is added. Using their methodology and allowing the highest possible R^2 to be 1.3 times the current value of 0.56, I find an adjusted estimate of 0.080. In addition, selection on unobservables would have to be 80 times as strong as selection on observables for the estimated effect of transfer percentage to be 0 - again showing that the estimated effect is very robust to potential omitted variable bias.

I also estimate the previous regression separately by the discipline of the class (STEM, humanities, social sciences, arts, other), to see whether the effect differs by the format of class typically used (e.g. lectures in STEM classes, discussions and seminars in humanities classes), and by the difficulty of the class, to see whether the effect size varies as students advance further in their major. Table A.7 presents the results by discipline. The effect is statistically the same in the humanities, STEM and in the social sciences. Only in art classes is the effect of transfer students negative, but the coefficient is not statistically significant. Table A.8 shows estimates based on whether the class is less advanced (lower division) or more advanced (higher division) and the estimated effect does not differ between the two.

While small, these estimates are on par with others found in the peer effects in higher education literature which are also typically small. For a one standard deviation increase in transfer percent (0.224), column 3 or 4 suggests that a direct admit's grade rises by 0.018 grade points, which is 2.3% of a standard deviation. Feld and Zölitz (2017) finds that a one standard deviation increase in average peer GPA causes a 1.26% of a standard deviation increase in own GPA. Golsteyn et al. (2021) finds that a one standard deviation increase in average peer persistence causes a 1.8% of a standard deviation increase in grades. Fairlie et al. (2024) finds that a one standard deviation increase in lab partner score causes a 6.6% of a standard deviation increase in own score. Zimmerman (2003) finds that a one standard deviation increase in peer verbal SAT score causes a 2.2% increase in own GPA. Carrell et al. (2009) finds that a one standard deviation increase in peer verbal SAT score causes a 8.3% increase in own GPA.

4.4 Discussion

The estimates in table 3 suggest that transfer students exert no negative effects on direct admits in their classes. This does not yet explain what exactly about transfer students matters, nor does it distinguish between the two possible reasons for positive effects - the effect of being positive role models or the effect of class curving.

As a first step towards understanding the results, I estimate the same regression but include other class characteristics, such as the percent of the class that is female or white. As transfer students are typically more likely to be first-generation college students or on financial aid, it is possible that the positive effect is really from these characteristics as students with these backgrounds are likely under-prepared and will perform worse. Table A.9 column 2 reports the results including class characteristics. The effect is indeed smaller but still positive and statistically significant, implying there is some aspect of the transfer student identity that matters separately from other background characteristics. To investigate the curve effect more, I also include the average lagged GPA of transfer students in the class. In majors with sequences of classes, transfer students tend to take them together unless they fail a class and need to retake it. Given this, a higher transfer percent is slightly positively correlated with higher transfer student GPAs. If the curve is a relevant effect, then I expect omitted lagged transfer GPA to have a negative bias on the effect of transfer percent. Indeed, I find a larger effect than before by including transfer student GPA (column 3 of table A.9).

Overall, it seems that there could still be two effects from having transfer students in classes. First, the curve does have an effect as transfer students tend to perform worse than direct admits, so having more transfer students in a class helps increase the grades of direct admits. Second, transfer students still exert some positive influence outside of the curve, as including lagged transfer student GPA led to a larger estimate. This positive influence is certainly separate from other aspects of their identity, suggesting that transfer students provide some positive peer effect specifically from their background of coming from another school. It is also plausible that all aforementioned effects are at play simultaneously, and that they happen to culminate into a small positive effect.

5 Intermediate Exposure Effects

Given the positive contemporaneous effect of transfer students, I now consider the cumulative effect of taking classes with transfer students. As direct admits take classes with more transfer students, it is possible that the positive effect is enough to help direct admits pass classes, thus helping them finish their given major (instead of being forced to exit the major) or graduate sooner. However, if transfer students do not help direct admits learn more, it is possible that being exposed to more transfer students over time leads to worse grades in follow-up classes, in particular when compared to a similar direct admit who took the same classes but with fewer transfer students. I now investigate this.

5.1 Identification

The regressor of interest is cumulative exposure to transfer students, which I calculate as the average of transfer percentage of all classes a student has taken over time. It is highly likely that this variable is endogenous as it relates to the various decisions students make each quarter when enrolling for classes. However, it is not possible to follow the same identification strategy I used for estimating contemporary effects as it involves controlling for aspects of each class a student took. To adapt it to this exercise would require controlling for a student's course history and aspects of each course, such as the professor and time of day, which leads to thousands of control variables.

Instead, I first estimate a reduced-form model for direct admits' grades on cumulative exposure to transfer students using controls primarily related to predetermined attributes. This includes major upon entry and the types of classes students took up to that quarter. Major upon entry will help determine the trajectory of courses the student chooses, and while I cannot control for exact course history, I use types of classes taken as an approximation. I also consider using other predetermined measures such as SAT and ACT scores and high school GPA. The ideal experiment would be to compare two direct admits with identical backgrounds, but one student took classes with more transfer students, and the other student took the same classes but with fewer transfer students. Given this, I also estimate a specification that includes demographics.

Finally, it is important to consider what else may explain the variation in cumulative transfer exposure beyond the two previously considered factors. More specifically, students who are more advanced upon entry will have higher exposure. For example, students who have more AP credits are eligible to skip introductory courses and take more intermediate courses, such as skipping introductory microeconomics for intermediate microeconomics. By skipping straight to an intermediate class, the student will have higher cumulative exposure earlier in their college career as they are taking more advanced classes typically taken by transfer students and direct admits in their sophomore, junior or senior year. These ambitious students are likely also more capable and will perform better as well. I control for this by including AP credits and a measure of how advanced a student's first quarter classes are by calculating the average quarter previous cohorts of direct admits would take those classes.

5.2 Empirical Strategy

I estimate the reduced-form effect of cumulative exposure to transfer students on direct admits' grades in a given class according to the following equation:

$$\begin{aligned} \text{Grade}_{ict} =& \beta \text{Transfer Exposure}_{i,t-1} + \theta \text{Entry Major}_i + \psi \text{Unit Types}_{i,t-1} \\ &+ \alpha \overline{\text{Q1 Class Difficulty}}_i + \gamma \text{AP Credits}_i + \zeta_c + \phi_t + \epsilon_{ict} \end{aligned} \tag{3}$$

where Grade_{ict} is the grade (on the 4.0 grade point scale) for student i taking class c at time t. $\text{Unit Types}_{i,t-1}$ is the lagged number of units counted separately by discipline and difficulty (upper vs lower division) as a proxy for course history and what point in their college career a student is in. $\overline{\text{Q1 Class Difficulty}}_i$ and AP Credits_i are controls for how advanced upon entry student i is. $\overline{\text{Q1 Class Difficulty}}_i$ is calculated by averaging over the average quarter previous cohorts of direct admits would take the classes chosen by student i in their first quarter. ζ_c is a class fixed effect as different classes curve to different average grades, and ϕ_t is a time fixed effect to control for grade inflation. $\text{Transfer Exposure}_{i,t-1}$ is the cumulative lagged transfer exposure for direct admit i, which is the average of transfer percentage values in all previous courses. β is the main coefficient of interest in the model. If students who take classes with more transfer students truly learn less, then I expect β to be negative.

To estimate equation 3, I trim my sample slightly by only considering students who enter between 2014-2016 and graduate or exit by Spring 2020. These are the only three cohorts of students in my data for whom I can accurately observe their cumulative transfer exposure from the very start.[16] I cut the sample by Spring 2020 and do not consider later cohorts to

[16] For the 2014 entering cohort, the cohort of direct admits that entered in 2011 would still be on campus and not be in my data. However, I expect freshman and seniors to share very few courses. Cutting the sample to only include the 2015 and 2016 cohorts leads to similar results (additional appendix table to be

Table 4: Cumulative Effect of Transfer Exposure on Grades

	Course Grade				
	(1)	(2)	(3)	(4)	(5)
Lagged Transfer Exposure	1.251***	-0.300***	-0.334***	-0.255***	-0.552***
	(0.039)	(0.071)	(0.070)	(0.066)	(0.044)
Baseline Controls		Yes	Yes	Yes	Yes
Class Selection Controls			Yes	Yes	Yes
Individual Characteristics				Yes	Yes
Lagged GPA					Yes
Average Outcome	3.424	3.424	3.424	3.424	3.424
	(0.738)	(0.738)	(0.738)	(0.738)	(0.738)
Average Lagged Transfer Exposure	0.098	0.098	0.098	0.098	0.098
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)
Observations	535,238	535,238	535,238	535,238	535,238
R^2	0.01	0.21	0.25	0.33	0.45

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in parentheses and clustered at the individual level. Observations are at the student-course level. Only observations for students who entered between 2014-2016 and graduated (or exited) by Spring 2020 and for classes that took place between Fall 2014 and Spring 2020 are considered. Individual characteristics include: ethnicity, age, gender, first generation status, Pell grant recipient status, origin, SAT and ACT test scores, and high school GPA.

avoid the effect of the COVID-19 pandemic.

5.3 Results

Table 4 displays the results of estimate equation 3, with standard errors clustered at the individual level. Column 1 does not include any controls. Column 2 is the full specification from equation 3. Columns 3 and 4 add the class selection controls (only for the course being considered) from the previous section and individual characteristics, respectively, to examine how the estimate changes. Column 1 initially reports a large positive effect, but this is mostly in part because of the types of classes taken by direct admits who are exposed to more transfer students, namely, classes in the humanities which have the highest transfer shares and have higher grades, while STEM has the lowest of both. By including course fixed

added). Because I have so few fully observed cohorts, I cannot leverage variation in transfer exposure across cohorts within major, as the previous literature has successfully done.

effects in column 2, the effect is now negative. The magnitude of the effect stays roughly constant in columns 3 and 4 as well.

To better understand the estimates, it is again more appropriate to frame them in terms of standard deviations. If lagged transfer exposure were to increase by one standard deviation, the estimate in column 2 would suggest that the student's grade would decrease by approximately 2.5% of a standard deviation. This estimate is thus very similar in effect to the estimate found in the previous section in regards to contemporaneous effects.

5.4 Discussion

The negative estimates in table 4 suggest that taking classes with more transfer students is actually detrimental for direct admits. Combined with the positive contemporaneous effects previously found, this would suggest that the benefit of transfer students mainly comes from getting higher grades due to the curve being more generous. When two similar students, differing only in their previous transfer exposure, take the same class, the student who has taken classes with more transfer students performs worse. To further adjust for the curve, column 5 of table 4 includes lagged cumulative GPA as an additional regressor to compare two students who appear similar in measured academic ability.[17] Indeed, after including lagged GPA, the estimated effect appears to almost double.

If students truly learn less, it is possible that this could be due to the transfer students directly or due to the instructor. Only one interviewed direct admit mentioned this, but it is possible that transfer students disrupt the flow of class by asking too many questions. It is also possible that instructors respond to this and purposely teach the class slower to compensate for the perceived lack of understanding from students. Students would then learn less and perform in related follow-up classes.

At this point, I have found suggestive evidence of negative effects of taking classes with transfer students. However, I also have strong evidence of positive contemporaneous effects. Combined with the fact that certain majors have sequences of classes that are recommended taken consecutively without breaks, it is not immediately clear what the effect on final GPA

[17]Lagged cumulative GPA is influenced by earlier transfer exposure, so this exercise is for descriptive evidence since including it is like using a post-treatment control.

could be. A direct admit who happens to start a sequence with many transfer students could have a higher GPA as a result of repeatedly taking classes with transfer students. They could, however, do worse in future classes, like electives, than if they never took those classes with transfer students.

6 Final Exposure Effects

Given the evidence so far, it is not immediately obvious what the effect of cumulative class exposure to transfer students has on final outcomes, such as time to degree or employment. The outcomes in this section can be split into two groups - academic final outcomes (final GPA, time to degree) and post-grad outcomes (internships, employment, income).

6.1 Identification

Similar to the previous section, it is not computationally feasible to adapt the identification strategy for contemporaneous effects to this setting. The same considerations noted in the previous section hold, as well as a new factor to consider.

As the main regressor of interest is final transfer exposure, it is important to consider not only how advanced students are upon starting university, as they will also have higher final exposure rates and likely better outcomes, but also the major(s) a student has throughout their college career. As majors in the humanities have higher transfer shares and grades, it was important to keep major at entry as a control for the previous regressions. Now, final transfer exposure is also related to the final major. For example, consider two direct admits in STEM, which has a higher rate of switching out.[18] If a student is adequately prepared for their STEM major, they will more likely stay in that major and be exposed to fewer transfer students. Now consider a student who is not prepared for the STEM major. They will likely perform worse and potentially switch majors willingly or because they do not meet the requirements for their major. As a result, they will have to switch majors, likely to the social sciences (see table A.10) which also has higher transfer shares than STEM and has

[18]See table A.10 - 60% of all direct admits switching disciplines is specifically students switching from STEM into social sciences or humanities.

worse outcomes in the labor market. Therefore, an increase in final transfer exposures may be correlated with worse performing direct admits.

As evidence of this phenomenon, table A.11 plots the result of estimating a regression of final transfer exposure on observables. Column 1 does not include major at graduation and there are statistically significant negative relationships between pre-university measures of ability (SAT score, ACT score, high school GPA) and final transfer exposure. This makes sense as better performing direct admits, who tend to choose STEM fields, should be able to stay in their initial majors if they want, and thus have lower final exposure rates. Worse direct admits will likely switch from STEM into social sciences and thus have higher exposure rates. When controlling for major at graduation (column 2), the previous negative effects become insignificant. In addition, the coefficient for AP credits is positive and statistically significant, as initially expected, once final major is included in column 2. As a result, results will likely show significant harmful effects between final transfer exposure rates and outcomes unless major at graduation is accounted for or an alternate identification and estimation strategy is used.[19] This will be particularly important for labor market outcomes, as final discipline will be a very important factor in finding employment or higher income jobs.

6.2 Empirical Strategy

To analyze effects on final outcomes, I estimate the following model:

$$\begin{aligned} \mathrm{Y}_i =& \beta \text{Transfer Exposure}_i + \theta \text{Entry Major}_i + \alpha \overline{\text{Q1 Class Difficulty}}_i \\ & + \Gamma \text{Academic Preparation}_i + \phi \text{Entry Year}_i + \kappa \text{Final Major}_i + \epsilon_i \end{aligned} \tag{4}$$

where Y_i is the outcome of interest (final GPA, time-to-degree in years, employment, and annual income). $\overline{\text{Q1 Class Difficulty}}_i$ is again the control for how advanced upon entry student i is. Academic Preparation$_i$ includes all pre-university measures of ability (test scores, high school GPA, AP credits). Entry major and year are also included as a rough proxy for the trajectory the student started with. Given the discussion in the previous

[19]As noted in the previous section, due to current data limitations I can only fully observe 3 cohorts of direct admits. Thus, I currently cannot leverage variation in transfer exposure across cohorts within major, as the previous literature has successfully done, until I receive more data.

subsection, I now include Final Major$_i$ as an additional control to account for the sorting of students into their major.[20] Transfer Exposure$_i$ is the final cumulative transfer exposure rate for direct admit i, which is the average of transfer percentage values in all courses. β is the main coefficient of interest in the model. If transfer students indeed have an overall negative effect on direct admits, then I expect β to be negative for all outcomes except time-to-degree, as spending less time to graduate could be beneficial (for instance, by saving money). Given the small estimates found in the previous sections, I also expect the estimates here to be similarly small in magnitude.

For this exercise, the conceptual experiment is to compare two students with similar pre-college academic preparation, such as test scores, AP credits, and initial major, who also graduate with the same majors. The academic preparation controls are all pre-determined before the student starts taking classes in their first term. The key identifying assumption then is that final major is an appropriate control variable, which is addressed in subsection 6.4, and that, conditional on all the control variables in equation 4, final transfer exposure is as good as random. Even after conditioning on these controls to compare two similar direct admits in terms of academic ability and interests, there is still leftover variation to identify β from the differences between students in terms of their exact course preferences.

To estimate equation 4, I trim my sample slightly by only considering students who enter between 2014-2016 and graduate by Spring 2020. As these outcomes only apply to students who graduated, I do not consider students who have left the university. For the post-graduation outcomes that use the First Destination Survey data, I use inverse propensity weights estimated via logit to account for response bias to the survey.[21] For the regression with employment as the outcome, I subset the sample to only include students who were interested in joining the labor force - that is, students who selected full-time employment, part-time employment, or seeking employment as their answer.

Table 5: Cumulative Effect of Transfer Exposure on Final GPA and Time to Degree

	(1)	(2)	(3)
Panel A. Effect on Final GPA			
Final Transfer Exposure	-0.164***	0.582***	0.527***
	(0.048)	(0.085)	(0.076)
Average Outcome	3.478	3.478	3.478
	(0.349)	(0.349)	(0.349)
R^2	0.00	0.33	0.35
Panel B. Effect on Time to Degree (Years)			
Final Transfer Exposure	-0.540***	-0.800***	-0.780***
	(0.048)	(0.101)	(0.102)
Average Outcome	3.984	3.984	3.984
	(0.323)	(0.323)	(0.323)
R^2	0.01	0.12	0.15
Main Specification		Yes	Yes
Demographics			Yes
Average Transfer Exposure	0.164	0.164	0.164
	(0.061)	(0.061)	(0.061)
Observations	15,191	15,191	15,191

Notes: *p<0.1; **p<0.05; ***p<0.01. Heteroskedasticity-robust standard errors are reported in parentheses. Observations are at the student level. Only observations for students who entered between 2014-2016 and graduated by Spring 2020 are considered. Demographics include: ethnicity, age, gender, first generation status, Pell grant recipient status, and origin.

6.3 Results

Table 5 presents the regression results from equation 4 for the academic outcomes.[22] Column 1 does not include any controls. Column 2 is the full specification from equation 4. Column 3 includes individual characteristics as a robustness exercise. Panel A shows the results for final GPA as the outcome, and panel B shows the results for time-to-degree as the outcome.

In panel A, the initial estimated effect is negative and significant, which would suggest that taking classes with transfer students is enough to lower overall grades. Once the full

[20] One may be concerned that including final major is inappropriate since it may operate as a mediator or endogeneous variable. I address this concern in subsection 6.4.

[21] Appendix tables for possible effects of transfer exposure on leaving the university, as well as survey nonresponse, to be provided soon.

[22] Tables 5 and 6 report results with heteroskedastictiy robust standard errors, as it is not immediately clear whether the standard errors need to be clustered, and if so, at what level.

specification is used in column 2 however, the effect is actually positive and larger. By comparing direct admits with similar academic preparation and the same starting and ending majors, taking classes with transfer students has a beneficial effect on final GPA. Adding demographics in column 3 does not appear to move the estimate significantly.

In panel B, the estimated effect is consistently negative and statistically significant in all columns. Including the main specification in column 2 leads to a slightly larger effect, and the estimate hardly changes in column 3 when demographics are added. Overall, this suggests that taking classes with more transfer students does help to graduate sooner. This does not explain why however. For instance, it could be that students are more likely to pass their classes and less likely to need to retake any, and thus can graduate sooner. It could also be that transfer students exert a positive peer effect in that they are role models with greater ownership of their education (though this channel seems unlikely given the lack of interactions between groups documented in the interviews).

Table 6 presents the regression results from equation 4 for the post-grad outcomes. Column 1 does not include any controls. Column 2 is the full specification from equation 4. Column 3 includes individual characteristics as a robustness exercise. Panel A shows the results for employment as the outcome, again only for students who signaled interest in joining the labor force, and panel B shows the results for income as the outcome.

Initial estimates suggest harmful effects until the main specification is included. In panel A, the initial estimate is fairly negative and significant. Once the main specification is included, however, the magnitude of the estimate is closer to zero and not statistically different from zero, although the standard errors are larger. Similarly, in panel B, the effect on income is initially negative and very large, but again once the main specification is included the magnitude is much smaller and not statistically different from zero, although the standard errors are once again larger.

6.4 Discussion

Overall, the main estimates in column 2 of tables 5 and 6 show that taking classes with transfer students is beneficial for academic outcomes and small negative effects for post-graduation outcomes. These estimates are from the main specification, which does include

Table 6: Cumulative Effect of Transfer Exposure on Employment and Annual Income

	(1)	(2)	(3)
Panel A. Effect on Employment			
Final Transfer Exposure	-0.349**	-0.087	-0.085
	(0.156)	(0.297)	(0.294)
Average Outcome	0.686	0.686	0.686
R^2	0.00	0.15	0.16
Observations	5,140	5,140	5,140
Panel B. Effect on Annual Income			
Final Transfer Exposure	-163,879.1***	-14,047.0	-9,683.2
	(13,419.5)	(19,220.2)	(19,222.2)
Average Outcome	60,304	60,304	60,304
	(38,023)	(38,023)	(38,023)
R^2	0.08	0.64	0.65
Observations	2,056	2,056	2,056
Main Specification		Yes	Yes
Demographics			Yes
Average Transfer Exposure	0.168	0.168	0.168
	(0.063)	(0.063)	(0.063)

Notes: *p<0.1; **p<0.05; ***p<0.01. Heteroskedasticity-robust standard errors are reported in parentheses. Observations are at the student level. Only observations for students who entered between 2014-2016, graduated by Spring 2020 are considered, and answered the First Destination Survey are included. Inverse propensity score weights are used to adjust for survey response bias. Demographics include: ethnicity, age, gender, first generation status, Pell grant recipient status, and origin.

final major as a control major. There is possible concern that final major is an endogenous control, in the sense that it is a control variable that is determined after the treatment - exposure to transfer students. To address this concern, I estimate the following logistic regression for the effects of transfer exposure on major:

$$\begin{aligned} P(\text{In Initial Major}_{i,t+1} = 1|\text{X}_{it}) = &\Lambda(\beta_1 \text{Transfer Exposure}_{i,t-1} + \beta_2 \text{Average Transfer Percent}_{it} \\ &+ \alpha \overline{\text{Q1 Class Difficulty}}_i + \gamma \text{AP Credits}_i + \phi \text{Quarter}_{it} \\ &+ \psi \text{Unit Types}_{it} + \theta \text{Entry Major}_i + \kappa \text{In Initial Major}_{it}) \end{aligned} \tag{5}$$

where Λ is the cumulative logistic distribution function and X_{it} are the regressors on the right-hand side. In Initial Major$_{it}$ is an indicator variable that equals 1 if student i is in their initial major at time t, AP Credits$_i$ and $\overline{\text{Q1 Class Difficulty}}_i$ are controls for how advanced a student is at entry, Unit Types$_{it}$ are the number of units counted separately by discipline and difficulty as a proxy for course history, and Quarter$_{it}$ are indicator variables for what quarter of school the student is in at time t, as in whether it is their first quarter, second quarter, etc. In this model, I include both lagged transfer exposure as well as the average transfer percent of all courses direct admit i is taking at time t. Whether the student is currently in their initial major or not is also a control variable in order to compare two students who are either both still in the same initial major or are both currently not in their initial major. In this model, both β_1 and β_2 are coefficients of interest. If taking classes with transfer students helps direct admits stay in their initial majors, for instance by getting higher grades, then I expect both coefficients to be positive.

Table 7 presents the results from estimating equation 5. Column 1 does not include any controls other than whether the student is currently in their initial major or not. Column 2 is the full specification from equation 5. Column 3 includes individual characteristics as a robustness exercise. In all three specifications, the coefficient for current average transfer percentage is positive and statistically significant. The coefficient for lagged transfer exposure is initial insignificant and negative, but once the main specification is included in column 2 the estimate is larger and statistically significant at the 10% level. Neither estimate changes significantly when moving from column 2 to column 3.

The estimates imply that the likelihood that a direct admit is in their initial major next period is indeed increased if their current set of classes has a higher average share of transfer students. To interpret these estimates, the estimate in column 2 means that if the average current transfer percentage increases by one standard deviation, then, relative to the baseline probability of 0.654, the probability of being in the initial major next period increases by 2.2 percentage points.[23] For lagged exposure, a one standard deviation increase leads to a 0.7 percentage point increase.

[23]A one standard deviation increase (0.133) leads to a change in the log-odds of 0.100548 (0.133*0.756). Exponentiating this leads to an odds ratio of 1.106. The baseline probability of 0.654 corresponds to odds of 1.89. Multiplying by the odds ratio gives odds of 2.09, which corresponds to a probability of 0.676.

Table 7: Cumulative Effect of Transfer Exposure on Being in Initial Major Next Quarter

	In Initial Major Next Quarter		
	(1)	(2)	(3)
Lagged Transfer Exposure	-0.198	0.530*	0.559*
	(0.174)	(0.299)	(0.302)
Current Average Transfer Percent	0.539***	0.756***	0.756***
	(0.077)	(0.107)	(0.105)
Currently in Initial Major	Yes	Yes	Yes
Main Specification		Yes	Yes
Individual Characteristics			Yes
Share in Initial Major	0.654	0.654	0.654
Average Lagged Transfer Exposure	0.098	0.098	0.098
	(0.061)	(0.061)	(0.061)
Average Current Transfer Percent	0.166	0.166	0.166
	(0.133)	(0.133)	(0.133)
Observations	165,489	165,489	165,489

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in parentheses. Observations are at the student-quarter level. Only observations for students who entered between 2014-2016 and for quarters between Fall 2014 and Spring 2020 are considered. Individual characteristics include: ethnicity, age, gender, first generation status, Pell grant recipient status, origin, test scores, and high school GPA.

While non-zero, the effect is fairly small, so final major is less of a potential mechanism for the final outcomes results and more of a significant omitted variable if it is not included. If anything, since transfer exposure helps direct admits stay in their initial major, which are mainly in STEM and have better employment outcomes, if one believes that transfer students really are harmful for the outcomes of direct admits outside of the major channel, then including final major should lead to more negative results. Instead, the estimates are closer to 0, showing how important it is to consider the sorting of students by including both initial and final major.

Column 2 of table A.12 shows the estimate of the effect on final academic outcomes without final major, and column 2 of table A.13 shows the estimate of the effect on final post-graduation outcomes without final major. For outcomes like final GPA and employment, one would conclude that transfer exposure has significant harmful effects on direct admits. In reality, the estimate is capturing the variation from less prepared students sorting out of

STEM. As there is only a small percentage increase in staying in one's initial major caused by transfer exposure, which makes the final major not a meaningful channel for the effect of transfer exposure, I consider the results without controlling for final major to be misleading.

6.5 Summary of Results

Overall, the main estimates in column 2 of tables 5 and 6 show that taking classes with transfer students is beneficial for academic outcomes and small negative effects for post-graduation outcomes. To better interpret these results, and summarize the previous results, table 8 presents all the main results. The table also displays the implied effect based on a one standard deviation increase in the treatment variable (relative to a standard deviation or the mean of the outcome). For example, in column 4, the effect of final transfer exposure on time-to-degree implies that a one standard deviation increase in transfer exposure leads to a 15.108% of a standard deviation decrease in time-to-degree, or a 1.225% decrease relative to the average time-to-degree of 3.984 years. Turning attention to the labor market outcomes, column 5 of table 8 means that a one standard deviation increase in transfer exposure leads to a 0.799% decrease in finding employment, relative to the average probability of finding employment of 68.6 percentage points, and a one standard deviation increase in transfer exposure leads to a 2.3% of a standard deviation decrease in income.

While small, these effects can have a meaningful impact for direct admits. Considering the policy debate discussed earlier about whether to increase the presence of transfer students or not, one possibility would be to remove the transfer program entirely. The last row of table 8 considers this exercise solely based on the estimates obtained.[24] On paper, direct admits would actually see a loss in terms of academic final outcomes - the average time-to-degree for direct admits would increase by 0.131 years and final GPA would decrease by 0.095 grade points. The 95% confidence intervals for these outcomes also rules out any null or positive effects. In terms of labor market outcomes, direct admits would see a 1.5 percentage point increase in finding employment and a $2,360 increase in income. The confidence intervals cannot rule out small negative effects or larger gains.

[24] This is not necessarily a counterfactual exercise, as such an exercise would have to consider what sort of student would replace the transfer students, or the effects of a smaller class size if there was no replacement.

Table 8: Summary of Main Estimates

	Outcome (Y)					
	Grade	Grade	Final GPA	Time-to-Degree (Years)	Employment	Annual Income
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	0.085***	-0.300***	0.582***	-0.800***	-0.087	-14,047
	(0.018)	(0.071)	(0.085)	(0.101)	(0.297)	(19,220)
Average Outcome	3.401	3.424	3.478	3.984	0.686	60,304
	(0.799)	(0.738)	(0.349)	(0.323)		(38,023)
Treatment (T)	Transfer Percent	Exposure	Exposure	Exposure	Exposure	Exposure
Mean(T)	0.165	0.098	0.164	0.164	0.168	0.168
	(0.169)	(0.061)	(0.061)	(0.061)	(0.063)	(0.063)
↑ SD(T) as % of SD(Y)	1.800	-2.480	10.172	-15.108		-2.327
↑ SD(T) as % of Mean(Y)	0.423	-0.534	1.021	-1.225	-0.799	-1.467
Remove Transfer Program	-0.014	0.029	-0.095	0.131	0.015	2,360
	[-0.020, -0.008]	[0.016, 0.043]	[-0.123, -0.068]	[0.099, 0.164]	[-0.084, 0.112]	[-3,969, 8,689]

Notes: The above table summarizes the main estimates from the previous exercises, as well as interpreting estimates in terms of standard deviations or the effect if there were no transfer students (in terms of units of the outcome) by multiplying the average treatment value by the coefficient. Standard deviations are reported in parentheses. The 95% confidence interval of the effect of removing transfer students is reported in the brackets.

Although the confidence intervals suggest that there are potentially larger gains in labor market outcomes for direct admits, it is important to keep in mind that this estimate comes from removing all transfer students from the campus. While not the focus of this paper, transfer students have significant gains by transferring to a four-year university and completing a bachelor's degree. Using the estimates from Light and Strayer (2004), for example, students who completed a bachelor's degree instead of finishing at an associate's degree saw a 7% increase in wages. There are also definitively harmful effects on direct admits' final GPA and time-to-degree if transfer students were removed. While increasing the presence of transfer students could have negative effects on direct admits' labor market outcomes, there are positive effects on direct admits' final academic outcomes, so increasing the presence of transfer students on campus does not seem to significantly harm direct admits.

7 Conclusion

In contributing to the active debate around transfer policies in the United States, this paper is the first to provide evidence of the peer effects of transfer students on direct admits for both academic and post-graduation outcomes. I use administrative data from one of the University of California schools to identify a small, positive causal contemporaneous effect of exposure to transfer students on direct admits' grades. Based on the negative estimates from cumulative exposure as well as results from my interviews with current students, this effect appears to predominantly occur through a 'curve mechanism' - as the average transfer student performs worse than the average direct admit, taking classes with more transfer students helps increase the direct admit's ranking and thus their grade. Although there are potential signs of learning loss, taking classes with more transfer students can help direct admits earn higher grades, which can help them stay in their initial majors, which then also reduces time-to-degree. Conditional on the initial and final major of students, the overall effect on GPA is positive. The effects on labor market outcomes also appear to be near zero and insignificant, albeit the standard errors are fairly large. In summary, given the positive on-paper effects on academics and how small all of the peer effects appear to be, I conclude that increasing the presence of transfer students in class does not harm direct admits.

As the first paper to examine these peer effects, there are some limitations that have yet to be resolved. Given the current dataset, these are the best estimates I am able to provide for the effect of cumulative exposure to transfer students. With more fully-observed cohorts, I could use initial major-cohort variation similar to that used in other peer effects papers like Hoxby (2000) to instrument for cumulative and final exposure.[25] The peer effects considered in this paper are only those that potentially take place in the classroom. Based on the student interviews, transfer students and direct admits are much more likely to interact outside of class, namely in student clubs and extracurricular activities like intramural sports. There is potentially more evidence of the positive role model peer effect in these settings.

This paper also only focuses on the outcomes for direct admits without considering the outcomes for transfer students. Given the unique setting, it is worth considering whether transfer students perform and behave similarly to transfer students in other schools across the United States. There is also the question of whether increasing the presence of transfer students is beneficial for other transfer students - the only two papers to have considered this, Ehrenberg and Smith (2004) and Nutting (2005), find conflicting results. In addition, it appears in my setting that transfer students are much more likely than direct admits to enter majors in social sciences and humanities, which have worse labor market outcomes than majors in STEM. Publicly available aggregate statistics on applications to the UC system show that this pattern also holds for applications - transfer students are more likely than direct admits to apply for majors in the social sciences and humanities. It is not immediately clear why this is the case, as this would suggest that transfer students purposely choose majors with worse outcomes, or that community college education does not provide enough preparation in STEM fields. This paper thus takes an important step towards an unanswered part of the debate about transfer students and transfer policies, but a great deal of work still remains to address other aspects of the debate.

[25] Appendix C provides initial findings looking into this approach and along with other instrumental variables I have considered.

References

Arcidiacono, P., Aucejo, E. M., & Hotz, V. J. (2016). University Differences in the Graduation of Minorities in STEM Fields: Evidence from California. *American Economic Review*, *106*(3), 525–562. https://doi.org/10.1257/aer.20130626

Baker, R. (2016). The Effects of Structured Transfer Pathways in Community Colleges. *Educational Evaluation and Policy Analysis*, *38*(4). https://doi.org/https://doi.org/10.3102/0162373716651491

Baker, R., Friedmann, E., & Kurlaender, M. (2023). Improving the Community College Transfer Pathway to the Baccalaureate: The Effect of California's Associate Degree for Transfer. *Journal of Policy Analysis and Management*, *42*(2), 488–524. https://doi.org/https://doi.org/10.1002/pam.22462

Barrios-Fernandez, A. (2023). Peer Effects in Education. *Oxford Research Encyclopedia of Economics and Finance*. https://doi.org/https://doi.org/10.1093/acrefore/9780190625979.013.894

Bianchi, N. (2020). The Indirect Effects of Educational Expansions: Evidence from a Large Enrollment Increase in University Majors. *Journal of Labor Economics*, *38*(3). https://doi.org/https://doi.org/10.1086/706050

Booij, A., Leuven, E., & Oosterbeek, H. (2017). Ability Peer Effects in University: Evidence from a Randomized Experiment. *The Review of Economic Studies*, *84*(2), 547–578. https://doi.org/https://doi.org/10.1093/restud/rdw045

Carrell, S. E., Fullerton, R. L., & West, J. E. (2009). Does Your Cohort Matter? Measuring Peer Effects in College Achievement. *Journal of Labor Economics*, *27*(3). https://doi.org/https://doi.org/10.1086/600143

Carrell, S. E., & Hoekstra, M. L. (2010). Externalities in the Classroom: How Children Exposed to Domestic Violence Affect Everyone's Kids. *American Economic Journal: Applied Economics*, *2*(1), 211–28. https://doi.org/10.1257/app.2.1.211

Carrell, S. E., Malmstrom, F. V., & West, J. E. (2008). Peer Effects in Academic Cheating. *Journal of Human Resources*, *43*(1), 173–207. https://doi.org/https://doi.org/10.3368/jhr.43.1.173

Cepeda, R., Buelow, M. T., Jaggars, S. S., & Rivera, M. D. (2021). "Like a Freshman Who Didn't Get a Freshman Orientation": How Transfer Student Capital, Social Support, and Self-Efficacy Intertwine in the Transfer Student Experience. *Frontiers in Psychology*, *12*, 155–188. https://doi.org/10.3389/fpsyg.2021.767395

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., & Newey, W. (2017). Double/Debiased/Neyman Machine Learning of Treatment Effects. *American Economic Review: Papers Proceedings*, *107*(5), 261–265. https://doi.org/10.1257/aer.p20171038

DeSimone, J. (2009). Fraternity Membership and Drinking Behavior. *Economic Inquiry*, *47*(2), 337–350. https://doi.org/https://doi.org/10.1111/j.1465-7295.2008.00121.x

Echelman, A. (2024, September). *Only 1 in 5 California community college students makes it to a university, audit says* (CalMatters, Ed.). Retrieved December 21, 2024, from https://calmatters.org/education/higher-education/2024/09/california-community-college-2/

Ehrenberg, R. G., & Smith, C. L. (2004). Analyzing the success of student transitions from 2- to 4-year institutions within a state. *Economics of Education Review*, *23*(1), 11–28. https://doi.org/https://doi.org/10.1016/S0272-7757(03)00078-5

Elliott, D. C., & Lakin, J. M. (2021). Unparallel Pathways: Exploring How Divergent Academic Norms Contribute to the Transfer Shock of STEM Students. *Community College Journal of Research and Practice*, *45*(11), 802–815. https://doi.org/10.1080/10668926.2020.1806145

Fairlie, R. W., Oliver, D. M., Millhauser, G., & Roland, R. (2024). Estimating Peer Effects among College Students: Evidence from a Field Experiment of One-to-One Pairings in STEM. *NBER Working Paper*, (33060). https://doi.org/10.3386/w33060

Feld, J., & Zölitz, U. (2017). Understanding Peer Effects: On the Nature, Estimation, and Channels of Peer Effects. *Journal of Labor Economics*, *35*(2). https://doi.org/https://doi.org/10.1086/689472

Feld, J., & Zölitz, U. (2022). The effect of higher-achieving peers on major choices and labor market outcomes. *Journal of Economic Behavior Organization*, *196*, 200–219. https://doi.org/https://doi.org/10.1016/j.jebo.2022.01.012

Fischer, S. (2017). The downside of good peers: How classroom composition differentially affects men's and women's STEM persistence. *Labour Economics*, 211–226. https://doi.org/https://doi.org/10.1016/j.labeco.2017.02.003

Flaga, C. T. (2006). The Process of Transition for Community College Transfer Students. *Community College Journal of Research and Practice*, *30*(1), 3–19. https://doi.org/10.1080/10668920500248845

Fletcher, J. M., & Tienda, M. (2008). High School Peer Networks and College Success: Lessons from Texas. *Working Paper*.

Fosnacht, K., Sarraf, S., Howe, E., & Peck, L. K. (2017). How important are high response rates for college surveys? *The Review of Higher Education*, *40*(2), 245–265. https://doi.org/https://dx.doi.org/10.1353/rhe.2017.0003

Genakos, C., & Kyrkopoulou, E. (2023). Social policy gone bad educationally: unintended peer effects from transferred students. *Centre for Economic Performance Discussion Paper*.

Golsteyn, B. H. H., Non, A., & Zölitz, U. (2021). The Impact of Peer Personality on Academic Achievement. *Journal of Political Economy*, *129*(4). https://doi.org/https://doi.org/10.1086/712638

Hills, J. R. (1965). Transfer Shock: The Academic Performance of the Junior College Transfer. *The Journal of Experimental Education*, *33*(3), 201–215. https://doi.org/https://doi.org/10.1080/00220973.1965.11010875

Hoxby, C. (2000). The Effects of Class Size on Student Achievement: New Evidence from Population Variation. *The Quarterly Journal of Economics*, *115*(4), 1239–1285. https://doi.org/10.1162/003355300555060

Jaggars, S. S., Rivera, M. D., & Buelow, M. T. (2023). Transfer Shock and Resilience: How Transfer-Related GPA Drop and Rebound Predict Student Departure from a Flagship University Campus. *Journal of College Student Retention: Research, Theory Practice*, *27*(1). https://doi.org/10.1177/15210251231163837

Jenkins, D., & Fink, J. (2016). Tracking transfer: New measures of institutional and state effectiveness in helping community college students attain bachelor's degrees.

Jones, T. R., & Kofoed, M. S. (2020). Do peers influence occupational preferences? Evidence from randomly-assigned peer groups at West Point. *Journal of Public Economics*, *184*. https://doi.org/10.1016/j.jpubeco.2020.104154

Key facts. (n.d.). *California Community Colleges Chancellor's Office*. https://www.cccco.edu/About-Us/Key-Facts

Lakin, J. M., & Elliott, D. C. (2016). STEMing the Shock: Examining Transfer Shock and Its Impact on STEM Major and Enrollment Persistence. *Journal of The First-Year Experience Students in Transition*, *28*(2), 9–31.

Lee, D. S., McCrary, J., Moreira, M. J., & Porter, J. (2022). Valid t-Ratio Inference for IV. *American Economic Review*, *112*(10), 3260–90. https://doi.org/10.1257/aer.20211063

Light, A., & Strayer, W. (2004). Who Receives the College Wage Premium? Assessing the Labor Market Returns to Degrees and College Transfer Patterns. *Journal of Human Resources*, (3), 746–773. https://doi.org/https://doi.org/10.3368/jhr.XXXIX.3.746

Machado, C., Reyes, G., & Riehl, E. (2025). The Direct and Spillover Effects of Large-Scale Affirmative Action at an Elite Brazilian University. *Journal of Labor Economics*, *43*(2). https://doi.org/https://doi.org/10.1086/726385

Marmaros, D., & Sacerdote, B. (2002). Peer andsocial networks in job search. *European Economic Review*, *46*, 870–879. https://doi.org/https://doi.org/10.1016/S0014-2921(01)00221-5

Miller, L. (2025). Switching Schools: Effects of College Transfers. *Working Paper*.

Monaghan, D. B., & Attewell, P. (2015). The Community College Route to the Bachelor's Degree. *Educational Evaluation and Policy Analysis*, *37*(1). https://doi.org/https://doi.org/10.3102/0162373714521865

Nutting, A. W. (2005). Do Community College Students Benefit When Transferring with Other Transfers?: A Cross-Section Peer Effects Analysis. *Working Paper*.

Oosterbeek, H., & van Ewijk, R. (2014). Gender peer effects in university: Evidence from a randomized experiment. *Economics of Education Review*, *38*, 51–63. https://doi.org/https://doi.org/10.1016/j.econedurev.2013.11.002

Oster, E. (2017). Unobservable Selection and Coefficient Stability: Theory and Evidence. *Journal of Business and Economic Statistics*, *37*(2), 187–204. https://doi.org/https://doi.org/10.1080/07350015.2016.1227711

Sacerdote, B. (2001). Peer Effects with Random Assignment: Results for Dartmouth Roommates. *The Quarterly Journal of Economics*, *116*(2), 681–704. https://doi.org/http://www.jstor.org/stable/2696476

Sacerdote, B. (2011). Peer Effects in Education: How Might They Work, How Big Are They and How Much Do We Know Thus Far? In *Handbook of the economics of education* (pp. 249–277, Vol. 3). Elsevier. https://doi.org/https://doi.org/10.1016/B978-0-444-53429-3.00004-1

Shi, L. (2023). Clearing Up Transfer Admissions Standards: The Impact on Access and Outcomes. *Journal of Human Resources*, *58*(6). https://doi.org/https://doi.org/10.3368/jhr.0721-11774R2

Shirley, M., Olsen, A., Kim, S., Dimino, M., & Kaplan, M. (2023). Heading in the Right Direction? Examining the Relationship of Transfer Patterns and Income Status on College Student Outcomes. *Research in Higher Education*, *64*, 808–833. https://doi.org/https://doi.org/10.1007/s11162-023-09729-8

Stinebrickner, R., & Stinebrickner, T. (2006). What can be learned about peer effects using college roommates? Evidence from new survey data and students from disadvantaged backgrounds. *Journal of Public Economics*, *90*(8-9), 1435–1454. https://doi.org/https://doi.org/10.1016/j.jpubeco.2006.03.002

Tasleem, R. (2024). New illinois law ensures university admissions for community college transfers. *BNN Breaking*. Retrieved January 9, 2024, from https://bnnbreaking.com/breaking-news/education/new-illinois-law-ensures-university-admissions-for-community-college-transfers/

The San Diego Union-Tribune (Ed.). (2012, May). *UCSD ends community college transfer guarantee*. Retrieved October 25, 2025, from https://www.sandiegouniontribune.com/2012/05/01/ucsd-ends-community-college-transfer-guarantee/

Thomas, L. (2025, August). *The transfer student advantage: soft skills in motion* (Times Higher Education, Ed.). Retrieved October 25, 2025, from https://www.timeshighereducation.com/campus/transfer-student-advantage-soft-skills-motion

Townsend, B. K. (2008). "Feeling Like a Freshman Again": The Transfer Student Transition. *New Directions for Higher Education*, *2008*(144), 69–77. https://doi.org/https://doi.org/10.1002/he.327

Transfer Opportunity Project. (2022). Transfer Shock: Longitudinal Analysis of Students who Transfer from Associate to Bachelor's Programs. *CUNY Office of Policy Research Research Brief*. Retrieved December 23, 2024, from https://www.cuny.edu/wp-content/uploads/sites/4/page-assets/about/administration/offices/oira/policy/research-briefs/TransferShockTOPBrief_July2022.pdf

Velasco, T., Fink, J., Bedoya, M., Jenkins, D., & LaViolet, T. (2024, February). *Tracking Transfer: Community College Effectiveness in Broadening Bachelor's Degree Attainment* (C. C. R. Center, Ed.). https://ccrc.tc.columbia.edu/wp-content/uploads/2024/02/tracking-transfer-community-college-effectiveness-1.pdf

Wilson, J. (2007). Peer Effects and Cigarette Use Among College Students. *Atlantic Economic Journal*, *35*, 233–247. https://doi.org/https://doi.org/10.1007/s11293-007-9064-z

Zimmerman, D. J. (2003). Peer Effects in Academic Outcomes: Evidence from a Natural Experiment. *The Review of Economics and Statistics*, *85*(1). https://doi.org/https://doi.org/10.1162/003465303762687677

A Additional Tables and Figures

Table A.1: Summary Table of All Students Over Time

	Entry Year							
	2012	2013	2014	2015	2016	2017	2018	2019
Female	0.55	0.57	0.57	0.56	0.58	0.58	0.58	0.58
White	0.27	0.28	0.28	0.27	0.26	0.27	0.27	0.27
Black	0.03	0.04	0.04	0.05	0.06	0.05	0.05	0.06
Asian	0.32	0.32	0.31	0.31	0.30	0.29	0.31	0.31
Hispanic	0.18	0.20	0.21	0.21	0.22	0.22	0.21	0.21
From California	0.78	0.79	0.79	0.79	0.81	0.79	0.77	0.80
Foreign	0.17	0.13	0.13	0.13	0.12	0.12	0.12	0.11
Transfer	0.36	0.33	0.35	0.35	0.34	0.34	0.35	0.36
First Generation College	0.22	0.23	0.23	0.23	0.23	0.23	0.22	0.21
First Generation Bachelor's	0.37	0.36	0.37	0.36	0.36	0.36	0.33	0.33
Pell Grant Recipient	0.42	0.41	0.42	0.40	0.40	0.39	0.36	0.36
SAT Score	1363	1365	1375	1369	1357	1359	1381	1386
	(147)	(148)	(149)	(155)	(158)	(155)	(154)	(151)
ACT Score	27.7	28.1	28.5	28.8	28.9	30.0	30.7	30.3
	(4.5)	(4.5)	(4.5)	(4.7)	(4.8)	(4.4)	(4.4)	(4.8)
Weighted HS GPA	4.21	4.29	4.31	4.33	4.33	4.36	4.39	4.42
	(0.34)	(0.33)	(0.32)	(0.33)	(0.31)	(0.32)	(0.33)	(0.31)
CC GPA	3.66	3.68	3.66	3.69	3.69	3.73	3.76	3.80
	(0.25)	(0.25)	(0.27)	(0.24)	(0.25)	(0.24)	(0.22)	(0.20)
AP Credit Units	17.6	20.4	20.3	20.8	20.9	22.1	23.6	24.9
	(19.7)	(20.5)	(21.3)	(21.4)	(21.5)	(21.7)	(23.2)	(23.6)
Entered Arts	0.04	0.04	0.04	0.04	0.03	0.04	0.04	0.04
Entered Humanities	0.13	0.11	0.11	0.11	0.11	0.11	0.11	0.10
Entered Social Sciences	0.35	0.37	0.36	0.37	0.36	0.36	0.35	0.36
Entered STEM	0.48	0.48	0.49	0.48	0.49	0.50	0.50	0.51
Did Not Graduate	0.07	0.07	0.07	0.07	0.06	0.07	0.07	0.07
Graduated in Arts	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Graduated in Humanities	0.12	0.10	0.11	0.11	0.10	0.10	0.09	0.08
Graduated in Social Sciences	0.39	0.42	0.40	0.40	0.39	0.37	0.36	0.36
Graduated in STEM	0.38	0.38	0.40	0.39	0.42	0.43	0.44	0.45
On-Time Graduation Rate	0.58	0.62	0.63	0.65	0.67	0.71	0.72	0.74
GPA at Graduation	3.27	3.30	3.34	3.35	3.38	3.44	3.52	3.60
	(0.50)	(0.50)	(0.48)	(0.49)	(0.47)	(0.48)	(0.46)	(0.43)
Cohort Size	8795	8520	8931	8788	9890	9206	9622	9159

Notes: Test score and high school GPA statistics are calculated only for direct admits. Community college GPA statistics are calculated only for transfer students. "Did Not Graduate" calculated as percentage of cohort that was not observed to have graduated by June 2024. Standard deviations are reported in parentheses.

Table A.2: Direct Entrants (D) vs. Transfer Students (T) Over Time

	Entry Year															
	2012		2013		2014		2015		2016		2017		2018		2019	
	D	T	D	T	D	T	D	T	D	T	D	T	D	T	D	T
Female	0.57	0.52	0.58	0.55	0.59	0.53	0.58	0.53	0.57	0.52	0.60	0.55	0.60	0.55	0.60	0.54
White	0.24	0.32	0.27	0.32	0.26	0.30	0.26	0.30	0.24	0.30	0.26	0.29	0.26	0.29	0.25	0.32
Black	0.04	0.03	0.04	0.03	0.04	0.04	0.05	0.04	0.06	0.05	0.05	0.06	0.06	0.05	0.06	0.05
Asian	0.34	0.29	0.35	0.26	0.34	0.25	0.34	0.25	0.32	0.25	0.32	0.25	0.35	0.23	0.36	0.23
Hispanic	0.18	0.17	0.19	0.20	0.20	0.22	0.20	0.22	0.22	0.21	0.22	0.23	0.19	0.23	0.21	0.22
From California	0.72	0.90	0.72	0.91	0.73	0.92	0.73	0.91	0.75	0.92	0.73	0.91	0.70	0.90	0.75	0.90
Foreign	0.18	0.15	0.11	0.16	0.12	0.15	0.11	0.15	0.11	0.15	0.11	0.15	0.10	0.16	0.09	0.15
First Generation College	0.20	0.26	0.21	0.28	0.20	0.29	0.20	0.29	0.21	0.27	0.20	0.29	0.17	0.29	0.17	0.27
First Generation Bachelor's	0.31	0.45	0.31	0.46	0.30	0.49	0.30	0.48	0.32	0.46	0.30	0.48	0.26	0.47	0.26	0.45
Pell Grant Recipient	0.36	0.53	0.37	0.50	0.35	0.54	0.34	0.51	0.35	0.49	0.33	0.51	0.30	0.46	0.31	0.46
Median Age	18.4	21.3	18.4	21.4	18.4	21.5	18.4	21.4	18.4	21.3	18.4	21.1	18.4	21.2	18.4	21.0
AP Credit Units	24.9	4.5	27.9	5.0	28.7	5.0	29.2	5.4	28.6	5.8	30.2	6.6	32.8	6.8	34.3	7.8
	(19.9)	(10.2)	(20.0)	(10.5)	(21.0)	(10.5)	(21.1)	(10.7)	(21.4)	(11.2)	(21.2)	(11.8)	(22.7)	(12.0)	(22.8)	(13.0)
Entered Arts	0.04	0.03	0.04	0.02	0.04	0.03	0.04	0.02	0.04	0.03	0.05	0.03	0.05	0.03	0.04	0.03
Entered Humanities	0.08	0.22	0.07	0.19	0.06	0.21	0.06	0.20	0.06	0.21	0.06	0.21	0.05	0.20	0.05	0.19
Entered Social Sciences	0.28	0.47	0.28	0.56	0.28	0.51	0.29	0.52	0.29	0.50	0.28	0.50	0.27	0.50	0.27	0.51
Entered STEM	0.60	0.28	0.61	0.22	0.62	0.26	0.60	0.26	0.61	0.27	0.62	0.26	0.63	0.27	0.64	0.28
Did Not Graduate	0.08	0.06	0.07	0.06	0.07	0.06	0.07	0.06	0.07	0.05	0.07	0.06	0.08	0.05	0.09	0.06
On-Time Graduation Rate	0.65	0.47	0.68	0.51	0.70	0.50	0.72	0.54	0.74	0.54	0.78	0.57	0.79	0.60	0.79	0.64
Time to Degree (Years)	4.17	2.42	4.14	2.35	4.11	2.36	4.08	2.32	4.05	2.30	3.99	2.25	3.97	2.22	3.94	2.17
	(0.70)	(0.83)	(0.63)	(0.77)	(0.60)	(0.73)	(0.51)	(0.73)	(0.46)	(0.61)	(0.42)	(0.56)	(0.41)	(0.52)	(0.34)	(0.49)
Graduated in Arts	0.04	0.03	0.04	0.02	0.04	0.02	0.04	0.02	0.03	0.02	0.04	0.02	0.04	0.02	0.04	0.03
Graduated in Humanities	0.07	0.21	0.06	0.19	0.06	0.19	0.06	0.19	0.05	0.19	0.06	0.20	0.04	0.19	0.03	0.17
Graduated in Social Sciences	0.35	0.45	0.37	0.53	0.35	0.48	0.35	0.49	0.34	0.48	0.31	0.48	0.30	0.48	0.29	0.48
Graduated in STEM	0.45	0.25	0.46	0.20	0.48	0.24	0.48	0.24	0.50	0.25	0.52	0.24	0.55	0.26	0.55	0.27
GPA at Graduation	3.28	3.25	3.31	3.28	3.35	3.30	3.38	3.30	3.41	3.32	3.49	3.34	3.56	3.44	3.62	3.56
	(0.50)	(0.51)	(0.49)	(0.50)	(0.47)	(0.49)	(0.47)	(0.51)	(0.47)	(0.48)	(0.45)	(0.52)	(0.45)	(0.48)	(0.41)	(0.46)
Cohort Size	5623	3172	5698	2822	5765	3166	5681	3107	6545	3345	6038	3168	6241	3425	5920	3280

Notes: "Did Not Graduate" calculated as percentage of cohort that were not observed to have graduated by June 2024 and can be students that dropped out of college or transferred out. Standard deviations are reported in parentheses.

Table A.3: Applicants by Student Type and Discipline

	Direct Admits	Transfer Students
Arts & Humanities	0.102	0.191
Social Sciences	0.250	0.484
STEM	0.475	0.325
Undeclared	0.173	0.000
Total Number of Applicants	756,820	165,773

Notes: This table displays the statistics for applicants for the entering years 2012-2019 by student type and discipline of major the applicants applied for. Statistics are calculated using publicly available aggregate data from the UC Office of the President. A very small number (less than 40) of transfer students applied specifically for the undeclared in social sciences option, so they have been added to the social sciences numbers. The economics department is classified as being part of the social sciences field.

Table A.4: First Destination Survey Respondent Demographics

	Survey Year								
	2014	2015	2016	2017	2018	2019	2020	2021	2022
Female	0.63	0.60	0.63	0.62	0.63	0.57	0.52	0.50	0.55
White	0.40	0.30	0.30	0.31	0.29	0.29	0.28	0.28	0.26
Black	0.04	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.04
Asian	0.27	0.27	0.36	0.35	0.32	0.34	0.37	0.37	0.39
Hispanic	0.20	0.18	0.16	0.18	0.17	0.17	0.15	0.15	0.16
From California	0.95	0.88	0.84	0.82	0.78	0.77	0.78	0.75	0.73
Foreign	0.05	0.17	0.11	0.09	0.14	0.13	0.11	0.13	0.11
Transfer Student	1.00	0.94	0.35	0.29	0.32	0.30	0.22	0.25	0.09
First Generation College	0.23	0.26	0.18	0.20	0.19	0.18	0.15	0.14	0.15
First Generation Bachelor's	0.47	0.45	0.33	0.33	0.32	0.30	0.26	0.23	0.23
Pell Grant Recipient	0.55	0.47	0.38	0.39	0.34	0.33	0.30	0.25	0.27
Response Rate of Transfer Students	0.08	0.55	0.19	0.21	0.24	0.32	0.12	0.13	0.61
Response Rate of Direct Admits	0.00	0.31	0.22	0.30	0.30	0.43	0.23	0.21	0.47
Responses	168	1586	1507	2206	2335	3336	1795	1648	2881

Notes: This table reports survey respondent demographics after merging the survey responses with the available student data. The survey is sent to students as they are graduating, which is why the first two years are primarily transfer students as the earliest cohort in the data is students who entered in 2012 and mainly transfer students would be expected to have graduated in 2014 and 2015. The last cohort is students who entered in 2019, so much fewer transfer students are expected to answer the survey in 2022. The decrease in response size in 2020 and 2021 is most likely due to the COVID-19 pandemic. The response rates by student type and year is calculated by dividing the number of respondents of that student type by the total number of students of that student type who graduated in that calendar year.

Table A.5: First Destination Survey Results for Direct Admits (D) vs. Transfer Students (T) Over Time

	Survey Year													
	2016		2017		2018		2019		2020		2021		2022	
	D	T	D	T	D	T	D	T	D	T	D	T	D	T
Employed	0.48	0.40	0.46	0.43	0.50	0.38	0.49	0.40	0.47	0.34	0.51	0.40	0.52	0.39
Full-Time	0.40	0.29	0.40	0.34	0.44	0.29	0.43	0.31	0.43	0.26	0.48	0.33	0.47	0.34
Part-Time	0.08	0.12	0.06	0.09	0.06	0.09	0.05	0.09	0.04	0.08	0.03	0.07	0.05	0.05
Seeking Work	0.18	0.26	0.21	0.28	0.20	0.32	0.22	0.28	0.21	0.31	0.14	0.22	0.16	0.30
In Grad School	0.19	0.13	0.17	0.11	0.18	0.11	0.17	0.10	0.23	0.20	0.27	0.24	0.18	0.14
Plan Grad School	0.13	0.17	0.15	0.16	0.11	0.15	0.09	0.16	0.09	0.13	0.07	0.13	0.12	0.14
Average Income	51,603	42,090	50,364	44,165	49,401	40,589	57,422	42,385	67,794	45,843	54,141	36,704	52,885	48,653
	(14,299)	(8,381)	(15,847)	(13,566)	(17,198)	(15,591)	(18,893)	(13,802)	(20,961)	(13,881)	(27,290)	(19,899)	(27,125)	(24,120)
Internships	1.42	0.81	1.42	0.80	1.87	1.03	1.81	0.94	1.94	0.97	1.75	0.90	1.69	0.76
	(1.20)	(0.94)	(1.27)	(0.97)	(1.32)	(1.08)	(1.29)	(1.05)	(1.25)	(1.08)	(1.27)	(1.10)	(1.27)	(1.02)
Response Size	986	521	1573	634	1593	742	2343	993	1403	393	1244	404	2626	255
Income Response Size	340	127	533	170	669	227	904	277	553	102	590	147	1294	99

Notes: Results above are calculated after adjusting for nonresponse bias to survey using inverse propensity weights. Income is reported in 2016 dollars and winsorized at the 99th percentile. Standard deviations are reported in parentheses.

Table A.6: Transfer Percentage Exogeneity Check

	(1)	(2)
Test Score	-0.5006***	-0.0072
	(0.0599)	(0.0127)
Missing Test Score	0.7086	0.0669
	(0.9820)	(0.1743)
AP Credits	-0.0069***	-0.0006
	(0.0022)	(0.0005)
Weighted High School GPA	-1.457***	0.0020
	(0.1411)	(0.0295)
Missing High School GPA	1.524***	0.0002
	(0.2197)	(0.0517)
Female	1.415***	0.0131
	(0.0707)	(0.0157)
Other Gender/Unknown	1.656	-0.0072
	(1.082)	(0.3146)
Age 20-21	12.82***	0.0307
	(0.0527)	(0.0247)
Age 22-23	15.56***	0.1214***
	(0.1237)	(0.0437)
Age 24+	16.02***	0.1717
	(0.6850)	(0.1653)
Pell Grant	0.3911***	0.0073
	(0.0955)	(0.0190)
American Indian or Alaskan Native	-0.5598	0.0274
	(0.5333)	(0.0988)
Asian or Pacific Islander	-1.152***	0.0028
	(0.0933)	(0.0199)
Black Non-Hispanic	0.0203	0.0473
	(0.1997)	(0.0368)
Foreign	-0.4408*	-0.0283
	(0.2307)	(0.0509)
Hispanic	0.0812	0.0152
	(0.1315)	(0.0261)
Other Ethnicity	-0.3640*	0.0484
	(0.1897)	(0.0399)
Not First Gen College	-0.1519	0.0162
	(0.1486)	(0.0285)
Unknown First Gen Status	0.4233	-0.0942
	(0.2729)	(0.0592)
Not First Gen Bachelors	-0.1160	-0.0179
	(0.1329)	(0.0263)
Asia	2.712***	0.2104
	(0.9845)	(0.2244)
Canada	3.167***	0.3770
	(1.071)	(0.2462)
Europe	0.9790	0.2893
	(1.054)	(0.2387)
Middle America	0.5016	0.3882
	(1.300)	(0.3218)
Middle East	0.7819	0.1586
	(1.039)	(0.2353)
Oceania	0.9070	0.1984
	(1.262)	(0.2811)
South America	-0.0457	0.2296
	(1.132)	(0.2602)
United States	2.017**	0.1651
	(0.9938)	(0.2247)
Class Selection Controls	No	Yes
Observations	1,155,990	1,155,990
R^2	0.16481	0.86947
Within R^2		0.00289
F-Statistic		1.83***
F-Statistic (With Age)		1.45*

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table reports the results of running a regression of transfer percentage in class (times 100) on observable characteristics of direct admits. Column 1 reports results without the class selection controls. Standard errors clustered at the course-time level are reported in parentheses. By including class selection controls in column 2, most variables except age become statistically insignificant, the within R^2 is very low, and the magnitude of the coefficients drops sharply. The joint significance of these coefficients is statistically insignificant at the 5% level if age is included. Including age in the main regression does not change results.

Table A.7: Contemporaneous Effect of Transfer Students by Discipline

	Course Grade					
	(1)	(2)	(3)	(4)	(5)	(6)
Transfer Percent	0.085***	-0.031	0.147	0.081**	0.105***	0.082**
	(0.020)	(0.038)	(0.095)	(0.037)	(0.035)	(0.034)
Class Selection Controls	Yes	Yes	Yes	Yes	Yes	Yes
Discipline	All	Arts	Other	Humanities	Social Science	STEM
Average Outcome	3.393	3.759	3.605	3.521	3.380	3.287
	(0.802)	(0.516)	(0.583)	(0.712)	(0.816)	(0.855)
Average Transfer Percent	0.29	0.19	0.26	0.30	0.34	0.17
Observations	1,089,105	76,137	3,678	189,075	316,960	503,255
R^2	0.23	0.23	0.23	0.23	0.23	0.23

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in parentheses and clustered at the course-time level. Observations are only for classes that took place between fall 2015 and spring 2020 and must be in a class with at least 10 undergraduates. All classes are split into: arts, humanities, social sciences, STEM, and other. The other category is primarily composed of military oriented classes. Estimates were found by interacting transfer percent with each discipline.

Table A.8: Contemporaneous Effect of Transfer Students by Difficulty

	Course Grade		
	(1)	(2)	(3)
Transfer Percent	0.085***	0.083**	0.086***
	(0.018)	(0.037)	(0.023)
Class Selection Controls	Yes	Yes	Yes
Sample	All Courses	Lower Division	Upper Division
Average Outcome	3.401	3.353	3.466
	(0.799)	(0.838)	(0.739)
Observations	1,089,025	622,165	466,860
R^2	0.24	0.24	0.24

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in parentheses and clustered at the course-time level. Observations are only for classes that took place between fall 2015 and spring 2020 and must be in a class with at least 10 undergraduates. All classes are split into upper or lower division, which is the terminology used by the university. Upper division classes are typically more advanced required class later in the major or elective classes, while lower division classes are introductory major classes or for a general audience.

Table A.9: Contemporaneous Effect of Transfer Students: Mechanism

	Contemporaneous Grade		
	(1)	(2)	(3)
Transfer Percent	0.084***	0.020	0.101***
	(0.019)	(0.023)	(0.037)
Lagged Transfer GPA			-0.037***
			(0.011)
Class Selection Controls	Yes	Yes	Yes
Class Characteristics		Yes	Yes
Average Outcome	3.399	3.399	3.399
	(0.803)	(0.803)	(0.803)
Observations	1,008,990	1,008,990	1,008,990
R^2	0.23	0.23	0.23

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in parentheses and clustered at the course-time level. Observations are only for classes that took place between fall 2015 and spring 2020 and must be in a class with at least 10 undergraduates. Class characteristics include the percentage of the class that is Female, White, Black, Asian, Hispanic, First-Generation College student, on financial aid, Foreign, and average age. Including lagged transfer GPA causes observations to be dropped when it is the first quarter that the transfer students enter, so they do not have a lagged GPA value. To keep the samples consistent, I keep the same sample for all three columns.

Table A.10: Sorting of Students by Discipline of Major

	Initial Discipline			
Final Discipline	Arts	Humanities	Social Sciences	STEM
Count	741	998	4,804	10,197
Arts	0.78	0.02	0.01	0.00
Humanities	0.03	0.39	0.06	0.03
Social Sciences	0.09	0.44	0.77	0.18
STEM	0.02	0.07	0.09	0.72
Leave	0.07	0.08	0.07	0.07

Notes: This table displays the probabilities, for a given initial discipline, that direct admits in the entering cohorts of 2014-2016 end in a certain discipline or leave the university. It also displays the number of direct admits from these cohorts that started in each discipline. For example, 10,197 direct admits started in a major in the STEM field, and 18% of them graduated with a major in the social science field instead. Based on counts, direct admits who switch specifically from STEM to social sciences actually account for 50% of all direct admits who switched disciplines. Direct admits who switch from STEM to humanities account for an additional 10% of switchers. The economics department is classified as being part of the social sciences field.

Table A.11: Correlations with Final Transfer Exposure

	(1)	(2)
Q1 Class Difficulty	0.0106***	0.0066***
	(0.0006)	(0.0004)
SAT Score	$-2.78 \times 10^{-5***}$	-2.06×10^{-6}
	(3.91×10^{-6})	(2.72×10^{-6})
Missing SAT	-0.0393***	-0.0040
	(0.0056)	(0.0039)
ACT Score	-0.0009***	-0.0001
	(0.0001)	(9.15×10^{-5})
Missing ACT	-0.0236***	-0.0028
	(0.0042)	(0.0028)
AP Credits	-1.49×10^{-5}	$7.46 \times 10^{-5***}$
	(1.93×10^{-5})	(1.4×10^{-5})
high school gpa weighted	-0.0078***	0.0003
	(0.0014)	(0.0010)
missing HS GPA	0.0011	-0.0010
	(0.0018)	(0.0013)
Female	0.0076***	0.0043***
	(0.0006)	(0.0005)
entry age	0.0013**	0.0014***
	(0.0006)	(0.0005)
Pell Grant	0.0044***	0.0028***
	(0.0008)	(0.0006)
American Indian or Alaskan Native	-0.0037	-0.0008
	(0.0043)	(0.0030)
Asian or Pacific Islander	-0.0070***	-0.0015***
	(0.0008)	(0.0006)
Black Non-Hispanic	-0.0008	-0.0044***
	(0.0019)	(0.0013)
Foreign	0.0010	0.0041***
	(0.0019)	(0.0015)
Hispanic	-0.0002	-0.0011
	(0.0012)	(0.0008)
Unstated/Unknown Ethnicity	-0.0062***	-0.0022*
	(0.0015)	(0.0011)
Not First Gen College	0.0009	0.0001
	(0.0013)	(0.0009)
Unknown First Gen Status	0.0049*	0.0017
	(0.0026)	(0.0019)
Not First Gen Bachelors	-0.0010	-0.0006
	(0.0011)	(0.0008)
Africa	-0.0156***	-0.0005
	(0.0060)	(0.0043)
Asia	0.0003	0.0038**
	(0.0019)	(0.0015)
Canada	-0.0067*	-0.0049
	(0.0038)	(0.0031)
Europe	-0.0037	0.0055**
	(0.0034)	(0.0026)
Middle America	-0.0039	-0.0045
	(0.0073)	(0.0057)
Middle East	-0.0051	0.0014
	(0.0032)	(0.0027)
Oceania	-0.0105	-0.0079*
	(0.0077)	(0.0047)
South America	-0.0093**	-0.0068*
	(0.0039)	(0.0040)
US not CA	0.0004	-0.0019***
	(0.0010)	(0.0007)
Entry Major and Year	Yes	Yes
Final Major		Yes
Observations	21,556	21,556
R^2	0.50167	0.75420

Notes: *p<0.1; **p<0.05; ***p<0.01. Heteroskedasticity-robust standard errors are reported in parentheses. The table above reports the estimates from regressing observables on final transfer exposure, without including major at graduation in column 1 and then including it in column 2. Observations are at the student level and only include direct admits who entered university between 2014-2016 and graduated by Spring 2020.

Table A.12: Cumulative Effect of Transfer Exposure on Academic Final Outcomes, With and Without Final Major

	(1)	(2)	(3)	(4)
Panel A. Effect on Final GPA				
Final Transfer Exposure	-0.164***	-0.054	0.582***	0.527***
	(0.048)	(0.055)	(0.085)	(0.076)
Average Outcome	3.478	3.478	3.478	3.478
	(0.349)	(0.349)	(0.349)	(0.349)
R^2	0.00	0.28	0.33	0.35
Panel B. Effect on Time to Degree				
Final Transfer Exposure	-0.540***	-0.506***	-0.800***	-0.780***
	(0.048)	(0.066)	(0.101)	(0.102)
Average Outcome	3.984	3.984	3.984	3.984
	(0.323)	(0.323)	(0.323)	(0.323)
R^2	0.01	0.11	0.12	0.15
Main Specification without Final Major		Yes	Yes	Yes
Final Major			Yes	Yes
Demographics				Yes
Average Transfer Exposure	0.164	0.164	0.164	0.164
	(0.061)	(0.061)	(0.061)	(0.061)
Observations	15,191	15,191	15,191	15,191

Notes: *p<0.1; **p<0.05; ***p<0.01. Heteroskedasticity-robust standard errors are reported in parentheses. Observations are at the student level. Only observations for students who entered between 2014-2016 and graduated by Spring 2020 are considered. Demographics include: ethnicity, age, gender, first generation status, Pell grant recipient status, and origin.

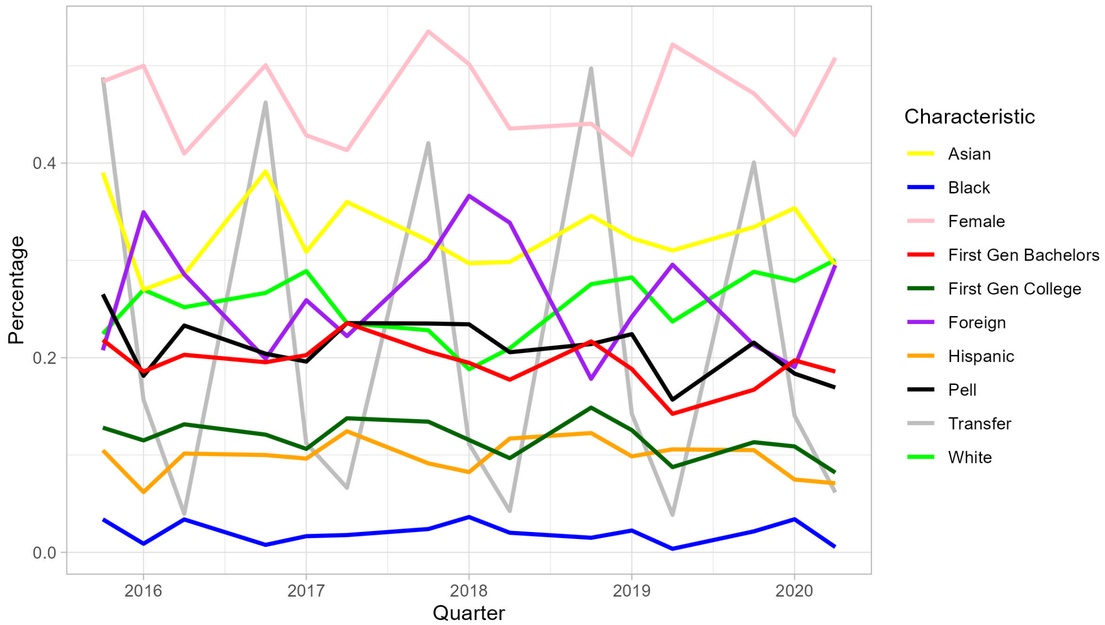
Table A.13: Cumulative Effect of Transfer Exposure on Post-Graduation Final Outcomes, With and Without Final Major

	(1)	(2)	(3)	(4)
Panel A. Effect on Employment				
Final Transfer Exposure	-0.349**	-0.519**	-0.087	-0.085
	(0.156)	(0.213)	(0.297)	(0.294)
Average Outcome	0.686	0.686	0.686	0.686
R^2	0.00	0.07	0.15	0.16
Observations	5,140	5,140	5,140	5,140
Panel B. Effect on Income				
Final Transfer Exposure	-163,879.1***	-31,660.7**	-14,047.0	-9,683.2
	(13,419.5)	(13,941.5)	(19,220.2)	(19,222.2)
Average Outcome	60,304	60,304	60,304	60,304
	(38,023)	(38,023)	(38,023)	(38,023)
R^2	0.08	0.52	0.64	0.65
Observations	2,056	2,056	2,056	2,056
Main Specification without Final Major		Yes	Yes	Yes
Final Major			Yes	Yes
Demographics				Yes
Average Transfer Exposure	0.168	0.168	0.168	0.168
	(0.063)	(0.063)	(0.063)	(0.063)

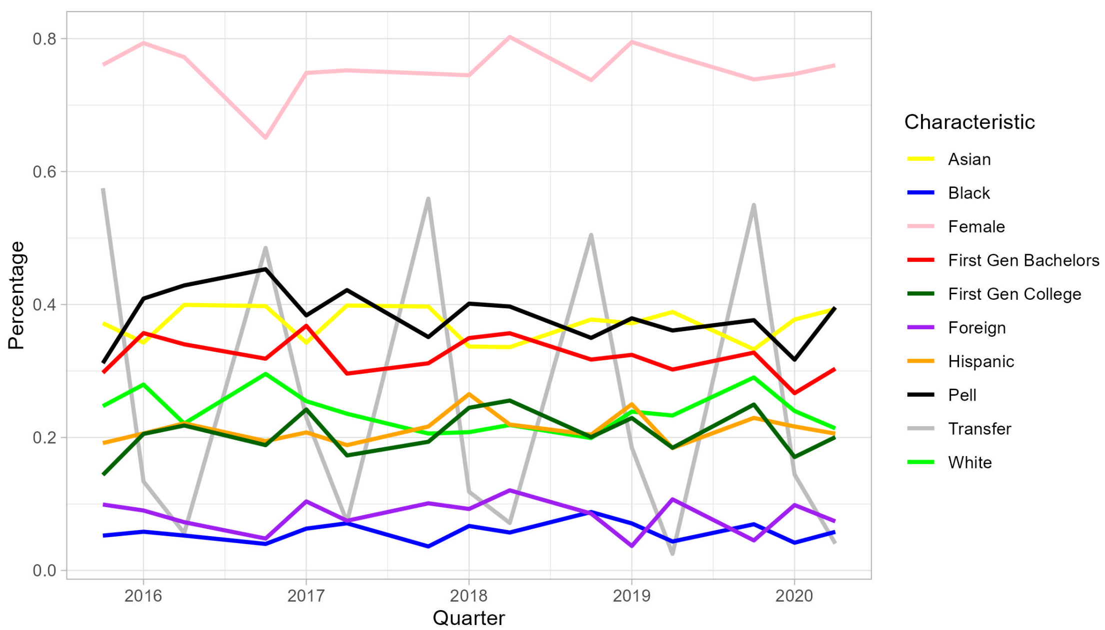
Notes: *p<0.1; **p<0.05; ***p<0.01. Heteroskedasticity-robust standard errors are reported in parentheses. Observations are at the student level. Only observations for students who entered between 2014-2016, graduated by Spring 2020 are considered, and answered the First Destination Survey are included. Inverse propensity score weights are used to adjust for survey response bias. Demographics include: ethnicity, age, gender, first generation status, Pell grant recipient status, and origin.

Figure A.1: Examples of Class Characteristics Over Time

(a) Intermediate Microeconomics I

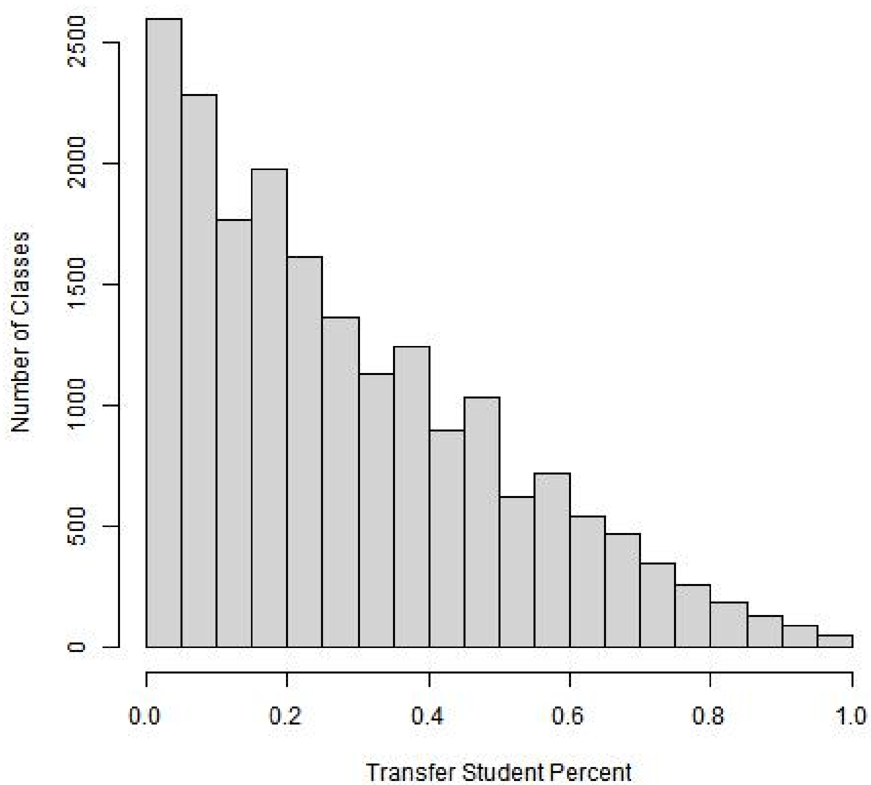


(b) Psychological Statistics



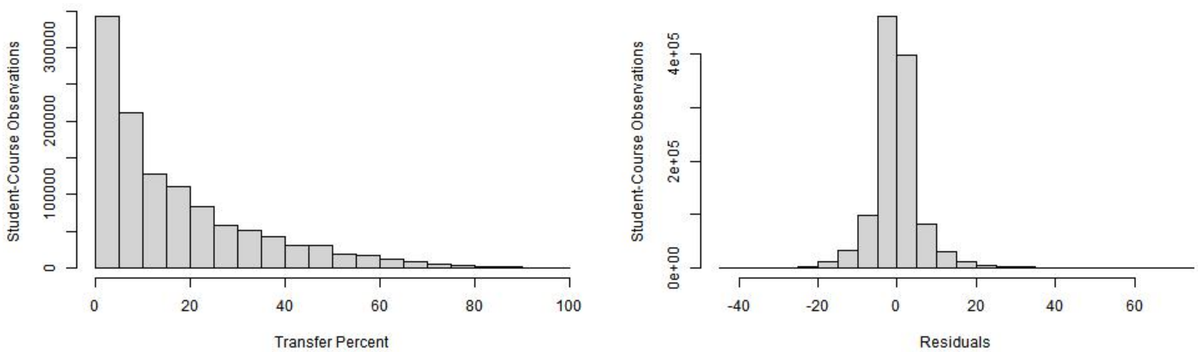
Notes: These figures plot the shares of different characteristics over time for two intermediate classes - one in economics and one in psychology. These classes are required for their respective majors and are the first class transfer students in each major would take. Other characteristics are roughly constant over time, while the percentage of transfer students shows a clear seasonal pattern - for these classes, it consistently spikes in the fall when a new cohort of transfer students enters.

Figure A.2: Distribution of Transfer Percentages by Class



Notes: This figure plots the distribution of transfer percentage of each class in the sample. The average percentage is 28.5%, with a standard deviation of 22.4%. Classes with less than 10 students are removed as there is no undergraduate class that would still meet with less than 10 students (These classes are typically research or thesis courses that students would register in for credit and are given pass/fail grades.).

Figure A.3: Distribution of Transfer Percentages at Observation Level



Notes: This figure on the left plots the distribution of transfer percentages at the observation (direct admit-course) level. The average is 16.5% with a standard deviation of 16.9%. The figure on the right is after residualizing by the class selection controls. The standard deviation is 6.1%.

B About the Interviews and Focus Groups

B.1 List of Questions

Background Questions for All Students

- Demographics/background
- age
- gender
- ethnicity
- place of origin
- major
- transfer student or not (yes/no)
- financial aid status (yes/no)
- last school they were at (high school or community college name)
- parents' highest level of education

Experience-Based Interview Questions for Transfer Students

- How did you do in high school?
- ask about academics, social life, goals, AP exams, GPA, and test scores if any
- Did you apply to 4-year colleges in high school?
  - If yes, which did you apply to, and were you accepted to any?If you were accepted to any, why not go?
  - If not, why not?
- Did you always plan to go to community college after high school?

- Did you do anything between high school and community college?
- How long did you spend at community college, how was it, and what was your GPA?
- Ask about academics, social life, and any employment while at community college
- Did you always plan to transfer from community college?
- How was the transfer preparation and application process?
- Did you have much guidance/advising?
- Did you apply to transfer to other schools? Did you use TAG?
- Did you lose any credits during transferring?
- How was the summer before transferring? Did you have time to do other things, like finding a job or internship if you wanted to?
- Do you think this school was a welcoming place for transfers? What about now?
- How was the first quarter here? How was the transition? Was it difficult relative to community college?
- Do you think you were adequately prepared to transfer/transition?
- Did you take any classes outside of your major, and if so why?
- Do you go to office hours?
- Are you still in the same major that you entered in? If not, what happened?
- Are you applying to jobs or internships?
- If so, how is/was the internship or job search?
- Are you considering graduate school? Have your plans changed since transferring?

Opinion-Based Interview Questions for Transfer Students

- Do you think there is any prejudice against transfer students? From direct admits? From faculty members or any academic department?
- Do you tell your classmates/friends that you are a transfer student? Do you tell professors or TAs?
- Do you notice other transfer students in your classes? Can you tell if someone is a transfer student or not?
- Do you feel that your identity as a transfer student has impacted your participation in extracurricular activities (e.g., student orgs, clubs, internships)? If so, how?
- How do you think of yourself compared to other students around you? Now how about compared to other transfer students? And compared to direct admits?
- Would you say your experience is similar to that of other transfer students that you know of? How so or why not?
- How would you describe your experience of transitioning from your previous institution, specifically in relation to your academic coursework? In relation to social or extracurricular experiences?
- What resources have you utilized here?
- What have you found to be most helpful, and in what areas do you feel resources are lacking?
- How would you describe your experience with your major's department faculty, TAs, and academic advisors? In what ways do these groups meet your needs/expectations as a student, and in what ways do they not?
- How would you describe your typical academic interactions with direct admit students? In the classroom? In study groups?

- How would you say that the transfer student community is differently equipped to excel than your non-transfer peers? In particular, do you find any unique advantages due to your prior academic experiences? If so, please elaborate.
- Do you think we should allow guaranteed transferring to schools like UCLA or UC Berkeley?

Experience-Based Interview Questions for Direct Admits

- How did you do in high school? ask about academics, social life, goals, AP exams, GPA, and test scores if any
- Did you consider the transfer pathway in high school? Why or why not?
  - If so, what would you have planned to do?
  - If not, why not?
- Do you have friends who did? What was their plan and why?
- How are you doing here? Ask about academics, social life, GPA, entry major
- Are you part of any clubs?
- What resources have you utilized?
- What have you found to be most helpful, and in what areas do you feel resources are lacking?
- How do you select your classes and when to take them? Describe all criteria and how important it is.

Opinion-Based Interview Questions for Direct Admits

- What do you think of the following student groups:
  - Older/Parents/non-traditional students
  - First-gen students

  - Financial aid students
  - International students
  - Transfer students
- Are you friends with any transfer students? Do you know any/many and how?
- Do you notice the transfer students here? What about in your classes?
- What do you think of transfer students as your classmates?
- What do you think of the transfer pathway in California?
- Do you think there should be a guaranteed transfer option to schools like UCLA or UC Berkeley? Why or why not? Would that have affected your college plans back in high school?

B.2 Summary of Responses

Table B.1: Summary Statistics for Interview Participants

	Direct Admits	Transfer Students
Female	4	8
White	3	7
Black	1	1
Asian	5	8
Hispanic	6	9
Foreign	2	4
From California	13	22
First Generation College	5	6
Pell Grant Recipient	8	14
Arts	1	0
Humanities	1	1
Social Sciences	5	22
STEM	5	2
Total Respondents	15	25

Notes: This table shows participant characteristics for the interviews and focus groups. Ethnicity is partitioned into the following categories: White, Black, Asian, Hispanic, and Foreign. Participants were found by emailing past students and asking if they would be open to answering questions about their experience at the university. Participants were only told afterwards that the overall project was specifically about how direct admits and transfer students interacted. This project was in collaboration with the economics department who were interested in evaluating their transfer program, hence many of the transfer students participants are in economics.

C Instrumental Variable Approaches

To resolve the endogeneity behind cumulative exposure to transfer students, I consider using an instrumental variables approach. For the instrument to be valid, it should be correlated with final transfer exposure, not be necessary for the main equation of interest, and itself be exogenous. To be exogenous in this setting would require that the instrument not be correlated with decisions made by the student over time. The instrument could therefore be something determined before starting university or determined solely in the first quarter, or the instrument could be determined by other student. With this in mind, I propose the following two instruments: initial quarter exposure to transfer students, and the leave-out-mean exposure to transfer students determined by other students in the same entering cohort and major.

C.1 Initial Quarter Exposure as an IV for Final Exposure

Initial quarter exposure to transfer students is the first candidate IV. It is not necessary for the main equations, and based on how transfer students tend to take classes together, a direct admit who happens to take classes with many transfer students in the first quarter is likely to continue encountering them in subsequent classes (recall Figure 2). This variable should also be exogenous as it is "pre-determined", in the sense that it is determined as soon as a student picks their first set of classes, which occurs at orientation before the first day of class.

One main concern would be that this measure is highly correlated with how ambitious the student is, as discussed in section 5.1. The main equation always include the average difficulty of initial quarter classes, so I argue that continuing to use this control should make this instrument conditionally exogenous. As supporting evidence, table C.1 reports the results of regressing initial quarter transfer exposure on observables, including and not including initial quarter class difficulty. Without including this control, many observables appear correlated with initial transfer exposure. By including this control in the second column, none of the observable are correlated and the test statistic for the overall significance of the observables is insignificant.

Table C.1: Correlations with Initial Transfer Exposure

Model:	(1)	(2)
SAT Score	$1.29 \times 10^{-5***}$	6.08×10^{-6}
	(4.22×10^{-6})	(3.87×10^{-6})
Missing SAT	0.0193***	0.0096*
	(0.0061)	(0.0056)
ACT Score	-0.0001	-0.0001
	(0.0001)	(0.0001)
Missing ACT	-0.0023	-0.0023
	(0.0043)	(0.0040)
AP Credits	-3.24×10^{-6}	-3.18×10^{-5}
	(2.32×10^{-5})	(2.12×10^{-5})
Weighted HS GPA	-0.0004	0.0008
	(0.0015)	(0.0014)
Missing HS GPA	0.0044**	0.0031
	(0.0022)	(0.0020)
Female	0.0008	0.0006
	(0.0007)	(0.0006)
Entry Age	-0.0008	-0.0005
	(0.0008)	(0.0007)
Pell Grant Recipient	0.0011	0.0005
	(0.0009)	(0.0008)
American Indian or Alaskan Native	-0.0050	0.0006
	(0.0041)	(0.0040)
Asian or Pacific Islander	0.0019**	0.0008
	(0.0009)	(0.0008)
Black Non-Hispanic	-0.0002	-0.0003
	(0.0018)	(0.0016)
Foreign	0.0043*	0.0017
	(0.0023)	(0.0021)
Hispanic	-0.0025**	-0.0014
	(0.0012)	(0.0011)
Unstated, Unknown, Other Ethnicity	0.0043**	0.0016
	(0.0018)	(0.0016)
Not First Gen College	0.0008	0.0006
	(0.0013)	(0.0012)
Unknown, Other First Gen Status	0.0068**	0.0019
	(0.0027)	(0.0025)
Not First Gen Bachelors	0.0009	-7.47×10^{-5}
	(0.0012)	(0.0010)
Africa	-0.0100	0.0007
	(0.0081)	(0.0061)
Asia	-0.0032	-0.0024
	(0.0023)	(0.0021)
Canada	-0.0148***	-0.0086***
	(0.0034)	(0.0030)
Europe	-0.0043	-0.0009
	(0.0040)	(0.0036)
Middle America	-0.0044	-0.0017
	(0.0083)	(0.0059)
Middle East	-0.0082**	-0.0031
	(0.0032)	(0.0029)
Oceania	-0.0044	-0.0005
	(0.0071)	(0.0070)
South America	-0.0175***	-0.0041
	(0.0052)	(0.0039)
US (not CA)	0.0004	-8.92×10^{-5}
	(0.0010)	(0.0009)
Entry Major and Year	Yes	Yes
Difficulty of Q1 Classes		Yes
Observations	15,191	15,191
R^2	0.17446	0.33471
F Statistic		1.19

Notes: *p<0.1; **p<0.05; ***p<0.01. Heteroskedasticity-robust standard errors are reported in parentheses. The table above reports the estimates from regressing observables on initial quarter transfer exposure, without including difficulty of initial quarter classes in column 1 and then including it in column 2. Observations are at the student level and only include direct admits who entered university between 2014-2016 and graduated by Spring 2020. The F-statistic reports the test statistic for joint significance of the observables in the table.

The variation for this instrument relies on students taking very different classes in their first quarter. However, by also controlling for the average difficulty of first quarter classes, it is possible there is not much variation in the instrument.

C.2 Entry Major Leave-Out-Mean Exposure as an IV for Final Exposure

The entry major leave-out-mean exposure is the second candidate IV. To calculate for a direct admit i, I calculate the leave-out-mean of final transfer exposure for all other students in the same cohort and initial major. It is not necessary for the main equations and is based on the decisions of other students who started in the same major and cohort. The variation in this instrument would rely on different shares of transfer students entering each year for a given major, which is similar to Carrell and Hoekstra (2010). In their setting, they study the effects of exposure to children exposed to domestic violence and their identification strategy relies on "idiosyncratic shocks in the proportion of peers from families linked to domestic violence within a particular school and grade over time" because they use school-by-grade fixed effects to control for nonrandom selection into schools.

One main concern would be that this measure is highly correlated with how many transfer students enter a given major. As shown in table 1, transfer students are more prevalent in the social sciences and humanities. I would therefore need to include entry major as a control. While in theory this is fine, in practice I unfortunately do not have enough fully observed cohorts to have sufficient variation in the major over time. To address this, I will instead use entry department as the additional control.

To accurately calculate leave-out-means, I remove observations where the number of students entering that major in a given year is less than 10. This mainly removes very small majors in the humanities.

C.3 Results

Tables C.2 and C.3 report the IV estimates analagous to tables 5 and 6, respectively. In both tables, column 1 reports the OLS estimate without final major, column 2 reports the OLS estimate with final major, while columns 3 and 4 are for the initial quarter exposure instrument, and columns 5 and 6 are for the leave-out-mean instrument. For columns 3-6, the IV regressions, final major is not included as the ideal regression would not include a post-treatment control.

For the academic outcomes in table C.2, both instruments are strong enough, even according to the cutoff rule of 104.67 as suggested by Lee et al. (2022). Both instruments agree in terms of sign and roughly in terms of magnitude for both outcomes. The IV estimates also line up (in sign) with the estimates previously found when major at graduation was included. The increase in standard errors is fairly high, which is expected given the controls necessary for the instruments to be plausibly exogenous and lack of data for variation in the second instrument.

For the post-grad outcomes in table C.3, the instruments are a lot weaker, likely due to the lack of responses to the survey. Initial quarter exposure is not strong enough according to Lee et al. (2022), but the leave-out-mean instrument still is for the internships and employment outcomes. The estimates from this second instrument are more in line with the estimates found in table 6 - namely near null effects for employment. For both instruments however the standard errors are much larger than before, making these estimates unreliable. For the final outcome, income, the first instrument is in fact no longer strong enough (greater than 10) so the estimates are omitted.

Table C.2: IV Estimates of Effect on Academic Final Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Effect on Final GPA						
Final Transfer Exposure	-0.054	0.582***	0.180	0.232	0.5349*	0.417
	(0.055)	(0.085)	(0.426)	(0.414)	(0.289)	(0.293)
Average Outcome	3.478	3.478	3.478	3.478	3.478	3.478
	(0.349)	(0.349)	(0.349)	(0.349)	(0.349)	(0.349)
IV F-stat			280	275	492	469
Panel B. Effect on Time to Degree						
Final Transfer Exposure	-0.506***	-0.800***	-1.839***	-1.850***	-1.179***	-1.113***
	(0.066)	(0.101)	(0.646)	(0.639)	(0.310)	(0.317)
Average Outcome	3.984	3.984	3.984	3.984	3.984	3.984
	(0.323)	(0.323)	(0.323)	(0.323)	(0.323)	(0.323)
IV F-stat			280	275	492	469
Entry Major and Year	Yes		Yes	Yes	Yes	Yes
Academic Preparation	Yes		Yes	Yes	Yes	Yes
Main Specification		Yes				
Demographics				Yes		Yes
Method	OLS	OLS	IV1	IV1	IV2	IV2
Average Transfer Exposure	0.164	0.164	0.164	0.164	0.164	0.164
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)
Observations	15,191	15,191	15,191	15,191	14,889	14,889

Notes: *p<0.1; **p<0.05; ***p<0.01. Heteroskedasticity-robust standard errors are reported in parentheses. Observations are at the student level. Only observations for students who entered between 2014-2016 and graduated by Spring 2020 are considered. IV1 corresponds to the initial quarter exposure, and IV2 corresponds to the entry major leave-out-mean exposure. Demographics include: ethnicity, age, gender, first generation status, Pell grant recipient status, and origin. For equations using IV2, I remove students who chose initial majors with less than 10 students in the same major and cohort. 1st stage F-statistics for the instruments are reported in IV F-stat.

Table C.3: IV Estimates of Effect on Post-Grad Final Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Effect on Employment						
Final Transfer Exposure	-0.519***	-0.087	-0.667	-0.892	-0.036	-0.024
	(0.213)	(0.297)	(2.693)	(2.522)	(0.841)	(0.857)
Average Outcome	0.686	0.686	0.686	0.686	0.686	0.686
Observations	5,091	5,091	5,091	5,091	5,007	5,007
IV F-stat			43	40	174	166
Panel B. Effect on Income						
Final Transfer Exposure	-31,600.7**	-14,047.0			-82,999.7*	-57,489.3
	(13,941.5)	(19,220.2)			(81,486.4)	(82,529.7)
Average Outcome	60,304	60,304	60,304	60,304	60,304	60,304
	(38,023)	(38,023)	(38,023)	(38,023)	(38,023)	(38,023)
Observations	2,056	2,056	2,056	2,056	2,045	2,045
IV F-stat			(low)	(low)	59	58
Entry Major and Year	Yes		Yes	Yes	Yes	Yes
Academic Preparation	Yes		Yes	Yes	Yes	Yes
Main Specification		Yes				
Demographics				Yes		Yes
Method	OLS	OLS	IV1	IV1	IV2	IV2
Average Transfer Exposure	0.168	0.168	0.168	0.168	0.168	0.168
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)

Notes: *p<0.1; **p<0.05; ***p<0.01. Heteroskedasticity-robust standard errors are reported in parentheses. Observations are at the student level. Only observations for students who entered between 2014-2016, graduated by Spring 2020 are considered, and answered the First Destination Survey are included. Inverse propensity score weights are used to adjust for survey response bias. IV1 corresponds to the initial quarter exposure, and IV2 corresponds to the entry major leave-out-mean exposure. Demographics include: ethnicity, age, gender, first generation status, Pell grant recipient status, and origin. For equations using IV2, I remove students who chose initial majors with less than 10 students in the same major and cohort. 1st stage F-statistics for the instruments are reported in IV F-stat.