

Nonresident Tuition and Human Capital Flows: Evidence from a Lottery

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Abstract

I use a pre-analysis plan and a computer-randomized lottery at a major American university to estimate the longer-run causal effects of nonresident tuition on the relocation of high-skill workers. Waiving nonresident tuition increases eventual migration by targeted students to the same state 12 years later, attracting workers with pre-specified innovation and executive skills. Every 10,000 dollars of tuition relief offered to nonresident students costs the institution 800 dollars in the short-run, but raises the net present value of longer-run estimated earnings from targeted students by 25,300 dollars within the local labor market. Migration effects are roughly as large as enrollment effects, reflecting increased retention of students who would have enrolled regardless. As a result, both the positive and negative long-run spillovers of nonresident tuition policies to locals are likely an order of magnitude larger than what would be inferred by assuming that only a fixed share of enrollees remain in-state.

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1 Introduction

Governments strategically enact policies to attract skilled workers, often targeting non-resident college students for their in-demand entrepreneurial, innovation, and executive skills (Prato, 2025; Adda et al., 2022; Bernstein et al., 2022; Amanzadeh et al., 2024; Lee et al., 2024; Martellini et al., 2024). Extant research on nonresident students typically focuses on the short-run trade-offs between nonresident tuition fees and crowd-out of local residents from capacity constrained programs, but questions about the longer-run labor market impact of nonresident tuition remain largely unanswered (Bound and Turner, 2007; Orrenius and Zavodny, 2015; Chen, 2021; Anelli et al., 2023). Understanding these long-run effects is crucial, as any welfare analysis hinges on the extent to which eventual migration alters the composition of the labor market.

Recent research highlights the need for longer-run causal estimates. Higher fees for domestic nonresidents can misallocate students across institutions, reducing aggregate welfare (Knight and Schiff, 2019), while lower fees for nonresidents may encourage students to transition into the local labor force, generating fiscal and labor market spillovers (Beine et al., 2023). Yet, despite growing nonresident enrollment and the potential to shape skilled migration, tuition decisions are often made without consideration or knowledge of these long-term effects (Groen and White, 2004; Bound et al., 2020).

Even absent evidence on how nonresident tuition shapes the labor market, colleges and universities are still obligated to adopt a policy. Public institutions often price discriminate on residency to balance their competing short-run financial and academic goals, with the uncertain trade-offs resulting in remarkable heterogeneity in their approaches. Some, like the University of Zurich and LMU Munich, have uniform tuition regardless of a student’s place of origin. Others like UC Berkeley and the University of Toronto price discriminate with supplemental fees even for domestic students from other national subdivisions. Understanding the causal effects of these choices requires exogenous variation in the fees of nonresident students, which is particularly difficult to come by at the individual-level given the scarcity

of financial aid programs that target them.

I advance this literature by using a pre-analysis plan and data from a computer-randomized tuition waiver lottery implemented in 2012 at a major North American research university.¹ Under the lottery, 1,333 international and domestic nonresident students from 45 countries who were admitted to the university were randomly assigned waivers that would reduce nonresident supplemental tuition by 20,000 dollars, 30,000 dollars, or 40,000 dollars over four academic years.² Students were tracked for more than a decade through the labor market and migration by linking names, birthdates, and academic records to the universe of publicly available LinkedIn profiles and American citizenship records from L2’s database of commercial data and state voter rolls. Individual-level random assignment in this setting is particularly important given that variation in nonresident tuition is often confounded by differences in admission or academic criteria.

I find that 12 years after applying to college, nonresidents who were offered lower tuition were more likely to live in the state where their tuition was discounted, increasing the number of workers with pre-specified executive and innovation skills in the state’s labor market. The high elasticity of student migration to tuition prices creates a sharp asymmetry between short-run higher education finance and longer-run fiscal externalities. Specifically, every 10,000 dollars in waived tuition costs the target university approximately 800 dollars in the short-run, but raises the net present value of long-run taxable earnings in the state where the university was located by 25,300 dollars.³ Pre-registered subgroup analyses offer some evidence for larger effects from STEM-focused students, with less heterogeneity by students’ place of origin.

This paper makes three contributions to the extant literature. First, it provides experi-

¹The campus is a member of the Association of American Universities (AAU), a group of 71 flagship research institutions in North America.

²Roughly one third of these students were American citizens or legal permanent residents at the time of college application. One fifth of all students who were “domestic nonresidents” – i.e. applicants who live in the United States, but are not authorized for in-state tuition – were not American citizens.

³In this context the short-run cost refers to the difference between net tuition paid by the student and the university’s instructional expenditures on the student.

mental estimates of the longer-run effects of nonresident tuition on skilled migration. Second, it quantifies the fiscal and labor market externalities of nonresident tuition, showing that universities’ pricing decisions likely have implications beyond their own budgets through nonresidents’ impact on local labor supply and wages (Kerr et al., 2015; Piyapromdee, 2021; Albert and Monras, 2022; Doran et al., 2022) as well as nonresidents’ impact on labor demand and innovation (Kerr and Lincoln, 2010; Peri et al., 2015; Dimmock et al., 2019; Azoulay et al., 2022; Brinatti et al., 2023). Third, it highlights how these effects interact with STEM immigration policies, shedding light on complementarities between reduced tuition and visa programs (Amuedo-Dorantes et al., 2020; Beine et al., 2023).

While the estimates in this paper focus on the direct effects of tuition waivers among admitted nonresident students, institutional decisions about pricing are made in tandem with admission. Unlike policies that expand nonresident enrollment by lowering academic thresholds, the lottery studied here varies tuition for students already admitted, allowing for causal identification on a clean willingness-to-pay margin. This distinction is important: reducing tuition for existing admits can raise long-run retention of students who already would have enrolled and generate fiscal and labor market externalities with lower risks of displacing local students or changing academic standards. More generally, while any reallocation of institutional resources could in theory have general equilibrium effects on in-state students, the randomization studied here holds both instructional capacity and local enrollment constant, isolating the migration effects of tuition itself. As such, the results should be interpreted as partial equilibrium estimates that inform one dimension of the broader policy trade-off in general equilibrium.

On balance, my results show that nonresident migration can be as sensitive as enrollment to tuition fees, with serious consequences for public finance and labor markets. There are large asymmetries between the incentives of colleges and governments, with increases in local labor market earnings more than an order of magnitude larger than the loss of revenue from targeted students. The response of skilled migration to tuition policies underscores a need

for better coordination between universities and policymakers in their efforts to strategically relocate skilled workers. Given the large negative price elasticity of *retaining* nonresident students who would have already enrolled, the long-run negative and positive externalities of nonresident tuition for local residents are an order of magnitude larger than what would be implied by assuming migration is a fixed fraction of nonresident enrollment.

2 The Tuition Waiver Lottery

Per my data agreement, I provide details about the policy setting but do not disclose identifying information about the university implementing the experiment, called the “target university”. The experiment in this paper was implemented by a member of the Association of American Universities (AAU), a group of North America’s top 71 research institutions. The target university has historically price discriminated on residency, charging uniform supplemental nonresident tuition fees to both international and domestic nonresident students. There is effectively no distinction in tuition policy between these two groups, with in-state residency defined primarily by the location of a students’ secondary school and the place of their legal guardian’s home address. Roughly one third of nonresident students were either American citizens or permanent residents at the time of application. Nonresident students are usually ineligible for need-based or merit-based financial aid at the target university, with under 10 percent of the sample offered any grant funding.

For the 2012-2013 academic year, administrators at the target university were interested in identifying the enrollment response of nonresident students to supplemental tuition fees and planned a computer-randomized lottery to assign tuition waivers of varying magnitudes. No application was required for eligibility and no selection criteria were applied beyond a requirement that students be admitted to the target university. From the full sample of 3,000 to 4,000 admitted nonresidents, the target university used a random number generator in Microsoft Excel to select 1,333 students to enter a tuition waiver lottery.⁴ The selected

⁴Unfortunately, administrators do not appear to have retained records on the students who were omitted

1,333 nonresident students originated from 44 countries and the United States and were randomly assigned to receive waivers that would reduce nonresident supplemental tuition fees by 20,000 dollars (444 students), 30,000 dollars (444 students), or 40,000 dollars (445 students) in nominal terms over the course of four academic years.⁵ The number of students subject to the lottery was chosen such that tuition waiver offers summed to a total of 10 million dollars. No other fringe benefits were associated with the program and there were no requirements to maintain the waiver other than remaining enrolled as a full time student in good standing.

Students were notified of the tuition waivers in the Spring of 2012 alongside their admission decisions from the target university. They were also separately notified with another award letter mailed to their home address on the same day. None of the materials stated the reason they were offered the tuition waiver or notified students of the existence of a randomized control trial with several treatment arms. No correspondence was necessary to claim the tuition waiver other than signalling intent to register at the target university before the college acceptance deadline and subsequently enrolling for the Fall 2012 term. If a student chose to enroll at the target university, their posted tuition fees would be reduced by the amount specified in their award letter when they entered their online payments portal. After this experiment, analysts at the target university concluded that the enrollment response of nonresident students to tuition prices was zero, citing a t-test from a small subsample of students. The tuition waiver program was discontinued in the following academic year.

This paper involves a secondary analysis of a computer-randomized RCT implemented by the target university in 2012. Prior to gaining access to any outcome variables other than target university enrollment, I pre-registered the project with a pre-analysis plan at the American Economic Association’s RCT registry as AEARCTR-0013117 ([Firoozi](#)). I link

from the lottery.

⁵The sticker price of tuition and fees for nonresidents was roughly 150,000 dollars in nominal terms over four years. Approximately 2/3rds of this was nonresident tuition and 1/3 was mandatory fees that also apply to local resident students. The three treatment arms discounted tuition at rates of 13%, 20%, and 27% of total tuition and fees, or 20%, 30%, and 40% of nonresident supplemental fees, or 40%, 60%, and 80% of the baseline of local resident tuition and fees.

original administrative data from the target university to high quality short-run enrollment records from the National Student Clearinghouse and longer-run outcome data from L2 Inc. and Revelio Labs. These pre-specified outcomes track students through immigration, employment, and the labor market.

3 Data and Methods

3.1 Data

This paper links four primary data sources at the individual level to track students from the time of their college applications, which were originally submitted in late 2011, through their longer-run outcomes in late 2024. I start by using administrative records from the admission and financial aid offices of the target university, which were retained for program evaluation. Records are then linked to National Student Clearinghouse data on the college enrollment history of students. Information on citizenship, labor market outcomes, and location come from the universe of American voter registration records supplied by L2 Inc. as well as the universe of public LinkedIn profiles supplied by Revelio Labs.

The individual-level administrative data used in this project come from the target university's admission and financial aid records in the 2011-2012 academic year and are linked using full name and date of birth to National Student Clearinghouse (NSC) data on higher education enrollment in the fall 2012 academic term. NSC data are detailed and highly accurate records on the near universe of higher education enrollment in the United States, covering over 95 percent of undergraduate student enrollment at 4 year colleges and universities in the United States. 72 percent of nonresident applicants in the sample are enrolled at a college or university in the United States in the fall term of 2012.

Voter registration records are sourced from L2 Inc., a private vendor of political and commercial data, for all American states and the District of Columbia in 2024. This data source is a close approximation to a full public registry of American citizens, covering more

than 75 percent of all American citizens. Voter registration data includes citizenship and location information, and the records were linked to the target university’s administrative data using students’ full names and dates of birth.

Labor market outcomes come from the universe of LinkedIn profiles scraped by Revelio Labs in 2024. This dataset includes job titles and descriptions, listed skills, profile summaries, and employment locations. Revelio Labs also imputes salaries based on job titles, employers, and employment history. Recent work in labor economics has found this dataset particularly useful for tracking populations of highly-mobile workers, including international students, across jobs and locations ([Amanzadeh et al., 2024](#); [Berry et al., 2024](#)). I link the target college’s administrative records to LinkedIn profiles matching on full name and manually review duplicates for any student who matches to 15 or fewer LinkedIn profiles. In cases where there are multiple matches on full name, students are manually matched to profiles using their college enrollment record as well as age cues that can be inferred from high school graduation date, the date of college entry and exit, and the earliest date of employment. I use pre-specified definitions for labor market outcomes derived from LinkedIn data that are described in this paper’s pre-analysis plan and are also summarized in [Appendix A](#).

[Appendix Table A.1](#) displays summary statistics for the full sample of lottery participants. Most of the nonresident applicants in the sample come from high socioeconomic status families, consistent with the characteristics we would expect given the high baseline cost of nonresident tuition fees. The mean family income reported by students is roughly 194,000 dollars per year, only 12 percent of the students were raised by a single parent, and just 20 percent are first generation college students. Other household and individual characteristics of nonresidents are similar to those of the university’s in-state students, like having a household size of around 4 people, entering college at roughly 18 to 19 years old, and a narrow majority of students identifying as female. With respect to place of origin, China is the largest source of nonresident students at approximately 45 percent, with 24 percent coming from students in adjacent American states, 10 percent from students in dis-

tant American states, 8 percent from South Korea, 9 percent from other countries in Asia and Oceania, 2 percent from other countries in the Americas, and just under 1 percent from Europe or Africa.

3.2 Randomization-based Inference

Because students were assigned to three treatment arms using a random number generator in Microsoft Excel, identification of causal effects follows from a simple comparison of the outcomes across treatment arms. I validate that randomization was successful by testing for balance on pre-treatment student demographics as well as predicted outcome variables. In Tables A.2 through A.9, I test for balance on observable characteristics like ethnicity, gender, GPA, and SAT score as well as predicted outcomes, finding only 5 rejections of the null hypothesis that the treatment arms are balanced out of 66 variables at a 90 percent confidence interval. The results of these pre-specified balance tests are, therefore, consistent with a normal rejection rate given successful randomization of students across the three treatment arms.

Beyond tests for balance, differential attrition is a potential threat to any RCT. Considering the risk of attrition, I note that students cannot attrit from binary decisions over whether or not to enroll in colleges and whether or not to live in the United States. The more serious attrition risk comes from students being unobservable in some types of outcome data. The research university’s enrollment data, voter registration records, and National Student Clearinghouse data on college enrollment are near complete records of their respective outcomes, averting this concern. However, some measures of long-run immigration and earnings from the universe of LinkedIn profiles provided by Revelio Labs will only cover students on the platform. I note that approximately half of students eventually appear either on LinkedIn or in the United States’ voter rolls and that there is no differential attrition across treatment arms.⁶ In the pre-analysis plan, I specify how incomplete data are handled for each respec-

⁶46 percent of students have location data available from either LinkedIn or L2’s dataset. Most missing

tive variable, including: deferring to complete administrative data on citizenship from voter files, combining information on student location from multiple data sources, and imputing some missing outcomes like earnings using pre-specified procedures.

Turning to Hawthorne effects and John Henry effects, I note that this tuition waiver lottery was effectively a single-blind RCT. All 1,333 in-sample students knew they had been offered a tuition waiver, but they were not aware that the value of the tuition waiver had been randomly assigned or that other students had been offered nonresident tuition waivers of different values than their own. Few of the nonresident students originated from the same high school, making it unlikely that they would have been able to identify one another or communicate with one another. The fact that all students received a waiver allows the estimates in this paper to exclude behavioral responses that would appear along the extensive margin of treatment with any tuition waiver, but are constant across the intensive margin of generosity. Students' incomplete information also means that there is little risk of spillover effects between lottery participants and the stable unit treatment value assumption (SUTVA) is likely to be satisfied.

To estimate causal effects, I use the following generalized specification:

$$Y_i = \beta \cdot Waiver_i + \mathbf{X}_i' \Gamma + \varepsilon_i, \quad (1)$$

where Y_i is an outcome of interest for student i , $Waiver_i$ is the net present value (in 2012) in tens of thousands of dollars of the tuition waiver assuming an annual discount rate of 5 percent, \mathbf{X}_i is a vector of pre-treatment controls including a constant term, and ε_i is an idiosyncratic error term. In this context, $\hat{\beta}$ is our estimate of the average treatment effect of 10,000 dollars of waived nonresident tuition on the respective outcome of interest. I plan to vary the inclusion of covariate controls for each outcome of interest and to use linear

location data occurs among students who choose to neither reside in the United States nor create a LinkedIn profile outside of the United States. There is no significant effect of tuition waiver size on appearing in the LinkedIn Data (t-statistic of -0.67) or appearing in any repository with location information (t-statistic of 0.10). To the extent that the overall rate of attrition is a concern, it should bias estimates toward zero by artificially shrinking differences in outcomes between treatment arms.

probability models for ease of interpretability with binary outcomes.

The estimated impact of nonresident tuition is likely to be a lower bound on the treatment effects because all of the 1,333 in-sample students applied to the university at its 2012 publicly-posted sticker price of nonresident tuition. If prospective nonresident students were to see lower sticker prices in 2012, that could increase both the number of applicants and admitted nonresident students making all outcomes of interest more sensitive to tuition prices than would be observed in this RCT. In the case of estimating tuition recovery, this will mean that higher enrollment elasticity to prices should be observed, biasing the short-run estimated tuition recovery of nonresident tuition upward and the longer-run costs of nonresident tuition downward.

4 Results

I estimate the impact of nonresident tuition waivers on short-run college enrollment decisions and longer-run measures of immigration and labor market earnings using the same set of variables that were specified in the pre-analysis plan (PAP) for this project. Deviations are noted in the text of the paper as well as in Appendix A. Although this should allay concerns about specification searching, I correct for multiple hypothesis testing, nonetheless, because of the number of outcomes being tested. Specifically, I use the Simes procedure to control for the false discovery rate and apply this correction within each specification for the full set of outcomes listed in the PAP. Adjusted q-values, which correspond to each respective p-value, are provided in each of this paper’s main tables.

4.1 Short-run

The first set of outcomes are short-run student decisions about college enrollment in the Fall 2012 academic term, a few months after receiving tuition waiver offers. Table 1 shows the estimated impact of tuition waivers per 10,000 dollars on binary indicators for

enrollment at the target university offering the waiver, enrollment at any college or university within the same state, and enrollment at any college or university within the United States. Each panel and row displays estimates for a single outcome while each column represents a different regression specification. Column 1 shows estimates without any control variables and Column 2 includes the full set of covariate controls described in Section 3.1.

Panel A shows that reducing nonresident supplemental tuition raises enrollment at the target university at a rate of roughly 3.2 percentage points per 10,000 dollars. As Panel B illustrates, this increases the total enrollment rate of nonresident students within the state of the target university by 4.9 percentage points.⁷ Both estimates are significant at a 95 percent confidence interval and are robust to including pre-treatment demographic control variables. In Panel C, I cannot reject the null hypothesis that total enrollment of nonresident students in the United States is unchanged, but the 1.6 percentage point estimate implies that roughly one half of the increase in enrollment at the target university came from students who would not otherwise choose to enroll at a college or university in the US. Results are again robust to the choice of whether or not to include pre-treatment controls.

In Appendix Table B.1, I examine how tuition waivers alter the types of institutions students attend. The results indicate that counterfactual enrollment is evenly split between three types of institutions: (i) private AAU universities, (ii) non-AAU public and private universities, and (iii) enrollment outside of the United States, each accounting for roughly one-third of the offset. This implies that the marginal student attracted by a waiver is typically weighing a diverse mix of alternative institutions with a variety of locations and qualities.

4.2 Longer-run

The next set of outcomes relate to the longer-run impacts of nonresident tuition on migration, the labor market of the target state, and the labor market of the United States.

⁷The slightly larger point estimate for enrollment in the target state may be explained by financial aid bargaining behavior (Firoozi, 2022).

With respect to the first set of outcomes, I estimate the impact of tuition waivers on a binary indicator for residence and citizenship, measured through voter registration in the target state and a binary variable for voter registration anywhere in the United States. With respect to the second set of outcomes, I identify the effects of nonresident tuition on the share of students with pre-specified skills based on their place of residence from LinkedIn and the L2 data.

In Table 2, I estimate the effects of nonresident tuition on appearing on the voter rolls of both the target state and the United States. Again, each panel includes results for a different outcome variable and the two columns show results for two different specifications with and without covariate controls. Column 1 of Panel A implies that every 10,000 dollars in tuition waiver offers raises the odds a student will be an American citizen who is registered to vote in the target state by 3.3 percentage points, a rate that is almost identical to the increase in enrollment at the target university and two thirds as large as the increase in total enrollment at any college or university in the target state.

The effect of tuition waivers on registration in the target state is driven entirely by students who were already citizens or permanent residents at the time of college application and remains significant at the 1 percent level when conditioning the outcome on being observed anywhere in the United States’ voter rolls.⁸⁹ Moreover, the treatment effect is much larger than what may be expected from evidence on the transition rates of nonresident students in Beine et al. (2023), implying that nonresident tuition changes relocation rates not only

⁸For comparison, enrollment outcomes were only somewhat larger for US citizens and permanent residents, but not to the degree that is observed for the longer-run relocation. For example, the point estimates are 3.8 percentage points compared to 2.8 percentage points for target university enrollment, which is not a significant difference at a 90 percent confidence interval, but may be economically meaningful. The result could be attributable to two phenomenon. First, US residents and citizens are more easily capable of freely choosing among states they live in than non-residents who are attempting to naturalize, which may be particularly true given that the non-residents who are attempting to naturalize will often rely on employment-related visas and would therefore be more constrained by location in their job search patterns. Second, It may simply be harder to observe the eventual outcomes like the location of nonresidents who are neither citizens or green cardholders, leading to estimated treatment effects that are biased toward zero. I note that in subsequent results, a more comprehensive pre-specified measure of long-run location including LinkedIn profiles is used to reduce missing data rates among such students.

⁹These robustness checks were not pre-specified as part of the original PAP. They demonstrate meaningful increases in the share of domestic nonresidents who relocate to the target state.

through higher college enrollment, but through raising the rate of longer-run relocation conditional on enrollment.¹⁰ In Panel B, I find positive but insignificant increases in citizenship and voter registration in the United States at 2.1 percentage points per 10,000 dollars, a rate that again closely matches the 1.6 percentage point rise in college and university enrollment in the United States and implies that roughly one third of counterfactual longer-run residency is outside of the United States.

Turning to the next set of longer-run outcomes, I estimate the impact of tuition waivers on a binary indicator for executive leadership skills and residence in the target state in 2024, a binary indicator for entrepreneurial skills and residence in the target state in 2024, a binary indicator for innovation skills and residence in the target state in 2024, and estimated earnings in the target state. Each of the first three outcomes was selected based on the high-demand skills held by college graduates described in [Martellini et al. \(2024\)](#) and are defined in Appendix A. Table 3 shows results for each outcome across rows and different specifications in each column, following the pattern of previous tables. Samples sizes in the first three rows are smaller than the full sample because the data come from the universe of LinkedIn profiles scraped by Revelio Labs and are set to missing for students who do not create a profile on the social media platform. Conditional on appearing in LinkedIn, the fraction of students with executive, entrepreneurial, and innovative skills are 73, 12, and 78 percent respectively.¹¹

Panel A shows the estimated impact of nonresident tuition waivers per 10,000 dollars on each of the three indicators for a student having one of the high-demand skills *and* residing in the state where they were offered a tuition waiver. Columns once again reflect different specifications that vary the inclusion of controls. Beginning with Row 1, I find that every

¹⁰I confirm this result by regressing longer-run residence in the target state on tuition waiver size among the subset of students who enrolled at universities in the target state and find a significant increase in appearing on the voter rolls of the target state at the 1 percent level. This result may be due to changes in students' choices of job offers after graduation, with students who faced a lower cost of attendance choosing jobs in the local labor market of the target state rather than more lucrative job offers elsewhere.

¹¹Consistent with the expectations set out in the pre-analysis plan, tuition waivers have no estimated impact on the probability that a student creates a LinkedIn profile and there is no association between measures of academic performance and the probability of creating a LinkedIn profile.

10,000 dollar reduction in nonresident tuition increases the share of nonresidents who hold executive skills in the target state in 2024 by 5.9 percentage points. Turning to Row 2, there is an insignificant 0.9 percentage point increase in the estimated migration of students with entrepreneurial skills to the target state. Finally, Row 3 shows another larger increase in the share of nonresident students who eventually hold innovative skills in the target state at a rate of 5.2 percentage points per 10,000 dollars. In every case, results are robust to the inclusion of controls for pre-treatment student demographics.

Panel B pivots to earnings in the target state, using estimated salaries based on job titles and employment history with imputed salaries for students with missing job titles, consistent with the PAP. I find that every 10,000 dollars of tuition waiver offers increases the present discounted value of earnings in the target state by 34,150 dollars, reflecting both the high elasticity of labor market mobility to nonresident tuition and the high earnings levels of students who are admitted to selective universities. These results remain significant, if somewhat smaller, at 25,300 dollars of earnings per 10,000 dollars of nonresident tuition when including pre-treatment control variables in the specification.

One potential mechanism linking tuition waivers to long-run earnings is degree completion. While the original pre-analysis plan included graduation outcomes, I was unable to observe graduation for students who did not enroll at the target university due to data constraints. Among the subset of students who did enroll at the target campus, I find that tuition waiver size has no significant effect on graduation and the point estimate is negative. This suggests that improved degree completion is unlikely to be the primary mechanism driving the observed earnings effects. However, I cannot rule out other unobserved academic adjustments, such as major choice or graduate school attendance, as possible channels linking tuition waivers to long-run labor market outcomes.

With respect to the final set of long-run outcomes, I estimate the impact of tuition waivers on a binary indicator for entrepreneurial skills and residence in the United States, a binary indicator for innovation skills and residence in the United States, a binary indicator

for executive leadership skills and residence in the United States, and estimated earnings in the United States. Table 4 displays results for each outcome using the outcome variables, methods, and specifications that mirror those in Table 3, but for the United States as a whole. In Panel A, I find insignificant impacts of nonresident tuition waivers on the number of executives, entrepreneurs, and innovators who eventually reside within the United States. Panel B shows positive but insignificant increases in earnings within the United States that are smaller than the corresponding estimates for earnings in the target state, implying that labor market benefits to one part of the US do not come exclusively at the expense of others.

5 Discussion

5.1 Fiscal Trade-offs

In this section, I use pre-specified methods to compare the short and longer run effects of nonresident tuition. Estimates of the short-run benefits focus on the recovery of tuition fees that both cover the costs of nonresident students and may be used in part to cross-subsidize local students. Estimates of the longer-run costs focus on the loss of taxable earnings and immigrants who generate positive externalities through their executive, entrepreneurial, and innovation skills. On balance, the results suggest that nonresident tuition at the target university is set at a level such that its marginal long-run fiscal costs exceed its positive short-run contribution to profit.

The primary benefit of nonresident tuition is the short-run recovery of profit, which I define in this case as net tuition less instructional expenditures, from nonresident students that may be used to cross subsidize the college attendance of local undergraduate students. To calculate profit, I begin by calculating total revenue. I assume that total revenue equals the net present value with a 5 percent annual discount rate of the total sticker price of tuition, less the randomly assigned tuition waiver for four years for nonresident students.¹²

¹²Tuition refers specifically to the sum of mandatory charges for nonresidents plus official nonresident

Profit then equals the difference between total revenue and the net present value, assuming a 5 percent annual discount rate, of instructional expenditures per capita from IPEDS for four years of instruction at the target university. Finally, I interact profit with an indicator for enrolling at the research university and use this measure as an outcome variable of interest to estimate the number of dollars recovered per 10,000 dollars of nonresident tuition. These procedures follow directly from the pre-analysis plan and as the pre-analysis plan states are likely to overestimate short-run profit.¹³

The primary longer-run external costs of nonresident tuition are the loss of target high-skill immigrants along with their attendant earnings and externalities. To address the former, I repeat my estimates for earnings from Section 4. To address the latter, I refer to the results for labor market mobility of executives and innovators from Tables 3 and 4. These methods likely underestimate the long-run cost of nonresident tuition, because they capture the elasticity of immigration to nonresident tuition conditional on application to the target university at a higher sticker price of nonresident tuition. Specifically, this is because the migration response to nonresident tuition will be underestimated if there is a negative college application elasticity to nonresident tuition.

I weigh these outcomes against one another in Appendix Table D.1, with the short-run benefits of nonresident tuition in Panel A and the external longer-run costs of nonresident tuition for both the target state and the United States in Panels B and C. Offering to waive 10,000 dollars of nonresident tuition only costs the target university 840 dollars due to both the low yield rate of nonresident students and the highly elastic response of nonresident enrollment to tuition prices. This result is consistent with the university having nonresident tuition prices set at a level that comes close to maximizing its short-run profit.

supplemental tuition fees, excluding other costs of attendance like housing, room and board, and books and excluding non-instructional fees for other student services.

¹³There are two reasons why this method is likely to overestimate the social benefits of nonresident tuition. First, this method will overestimate tuition recovery because the tuition lottery occurred among students who were already admitted and therefore recovers a lower bound on the elasticity of enrollment to prices by missing out on the elasticity of application rates to prices. Second, it overestimates tuition recovery because it assumes students pay net tuition fees over a four year time period, rather than assuming that some number of students drop out.

However, the policy of charging higher tuition to nonresident students seems to come at a steep long-run cost to the state in which the target university resides. For every 10,000 dollars of nonresident tuition waived, the net present value of earnings in the state rises by 34,150 dollars. This means that the forgone net present value of earnings from nonresident students are more than an order of magnitude larger than the university's profit, even assuming that students will only be employed for 20 years, that their earnings do not grow, and after discounting at a 5 percent annual rate. Although the results for the United States as a whole are noisier, the 14,640 dollars increase in the net present value of earnings is again an order of magnitude larger than the short-run recovery of profit.

These results are robust across specifications. More conservative approaches to this comparison also lead to the same conclusion. Assuming a 5 percent state-level tax rate on earnings and 25 percent federal tax rate on earnings suggests that tax revenue in the target state and United States would rise by 1,760 dollars and 3,660 dollars for every 840 dollars of forgone tuition. It is worth noting that this approach omits the net increase in workers with executive and innovation skills, which itself may have fiscal externalities or complementarities with the state's labor market that are not captured through the measurement of nonresident student earnings alone.

As a caveat, this framework compares institutional tuition revenue against longer-run state earnings and fiscal spillovers. It does not account for potential general equilibrium effects on in-state students. If attracting additional nonresident students strains instructional capacity or displaces local students, this could dampen the estimated gains. For instance, reduced enrollment opportunities for in-state students might lower their degree attainment or long-run taxable earnings, partially offsetting the fiscal benefits of retaining high-skilled nonresidents. Alternatively, expanding total enrollment to accommodate nonresident students could introduce negative cohort effects, as discussed in [Bound and Turner \(2007\)](#). I cannot directly test these spillovers given the design of the original lottery, which was implemented conditional on admission. Nonetheless, I acknowledge that any comprehensive

welfare analysis should weigh not only the gains from marginal nonresident students, but also the possible downstream costs or benefits for local students. The estimates presented here should therefore be interpreted as partial equilibrium effects that hold local enrollment fixed.

5.2 Non-linearity

While the main analysis estimates effects linearly across waiver amounts, disaggregating by treatment arm reveals meaningful nonlinearity in Appendix B. Enrollment at the target university reflects a convex demand curve. Migration, labor market, and fiscal externalities by contrast are largest for the 30,000 dollar treatment group, with smaller or flat marginal returns at 40,000 dollars. These patterns suggest that the effects of nonresident tuition waivers are not driven solely by enrollment expansion, but also by the retention of students who would have otherwise left the state after graduation. Moreover, the correspondence between enrollment, migration, and labor market outcomes implies that willingness to pay varies meaningfully across different nonresident student populations, with the highest skill students concentrated among those with a higher willingness to pay and on the margin of retention. This nonlinearity suggests the existence of an optimal nonresident tuition level that maximizes long-run public benefits while minimizing short-run institutional cost.

5.3 Heterogeneity

Consistent with the pre-analysis plan, I test for heterogeneity by place of origin and by intention to major in STEM disciplines. In Appendix C, I do not find significant heterogeneity between domestic nonresidents and international students. By contrast, point estimates for intended STEM majors are several times larger than those for non-STEM majors, consistent with their higher earnings levels and greater ease of migration to the United States.

6 Conclusion

This paper offers evidence from a computer-randomized lottery on the short-run and long-run impact of nonresident tuition on college enrollment choices, migration, and labor market outcomes. I use a pre-registered pre-analysis plan and data on 1,333 students subject to a tuition waiver lottery over a 12 year time period. My results highlight the trade-offs between short-run tuition revenue for universities and the longer-run labor market externalities that accrue to the state in which the university is located.

In the short run, reducing nonresident supplemental tuition significantly increases enrollment at the target university and within the state, demonstrating a high elasticity of nonresident student enrollment to prices. The estimates also underscore the potential for tuition waivers to attract nonresident students who might not have considered enrolling otherwise, with half of such students having counterfactual enrollment outside of the United States.

In the longer run, reducing nonresident tuition has large impacts on migration and labor market outcomes. Higher rates of long-run residency in the target state are observed even conditional on students' college enrollment choice. The substantial positive effects on earnings and the residency of workers with in-demand executive leadership and innovation skills highlight plausible externalities that extend beyond the duration of students' academic careers.

Pre-specified heterogeneity analyses indicate that these effects are relatively consistent across place of origin. However, stronger impacts among students with STEM major intent highlight the complementarity of policies that ease the bureaucratic and direct financial costs of immigration.

Importantly, the design of the tuition waiver lottery isolates the treatment effects along the willingness-to-pay margin among already-admitted students, distinguishing these findings from those that would arise from expanding nonresident admission more broadly. Because the lottery does not change admission standards or identify spillovers to local students,

the estimated effects capture the migration and labor market consequences of tuition pricing alone, holding institutional capacity and local student access constant. As such, the results should be interpreted as partial equilibrium estimates that inform one major component of the broader general equilibrium trade-offs.

The results of this paper illustrate asymmetric trade-offs between institutional and government objectives. While the short-run financial goals of colleges may lead them to recover tuition revenue from nonresidents, the longer-run costs of reduced retention among high-skill students, manifested through foregone taxable earnings and labor market externalities, are not internalized. My findings suggest that better aligning university pricing strategies with state-level migration and fiscal goals, particularly on the pricing (rather than admission) margin, could enhance the effectiveness of policies aimed at attracting *and retaining* skilled workers. In doing so, policymakers can use nonresident tuition as a tool for long-run labor market development with less of risk displacing local students or changing academic standards.

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Tables

Table 1: Enrollment Effects of Nonresident Tuition Waivers per 10,000 Dollars

Outcome	(1)	(2)
<i>A. Enrollment at Target University</i>		
	<i>[Baseline: 0.1622]</i>	
Target University	0.0315**	0.0345***
	(0.0148)	(0.0129)
p-value	[0.0337]	[0.0076]
q-value	[0.0506]	[0.0187]
<i>B. Enrollment Anywhere in the Target State</i>		
	<i>[Baseline: 0.4167]</i>	
Any Target State College	0.0489***	0.0523***
	(0.0188)	(0.0189)
p-value	[0.0093]	[0.0057]
q-value	[0.0187]	[0.0187]
<i>C. Enrollment Anywhere in the United States</i>		
	<i>[Baseline: 0.6779]</i>	
Any US College	0.0156	0.0110
	(0.0175)	(0.0173)
p-value	[0.3724]	[0.5257]
q-value	[0.4468]	[0.5257]
Controls	No	Yes
Sample Size	1,333	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses. P-values are shown for each estimate in brackets in the row titled “p-values”. Adjusted q-values from the Simes procedure to correct for multiple hypothesis testing are for each estimate in brackets in the row titled “q-values”. “Baseline” refers to the mean value of the outcome variable for the smallest tuition waiver treatment arm (\$20,000).

Table 2: Migration Effects of Nonresident Tuition Waivers per 10,000 Dollars

Outcome	(1)	(2)
<i>A. Registered in Target State after 12 Years</i>		
	<i>[Baseline: 0.0608]</i>	
Registered in Target State	0.0329*** (0.0108)	0.0268** (0.0105)
p-value	[0.0023]	[0.0109]
q-value	[0.0093]	[0.0218]
<i>B. Registered in the United States after 12 Years</i>		
	<i>[Baseline: 0.2005]</i>	
Registered in United States	0.0213 (0.0157)	0.0121 (0.0122)
p-value	[0.1745]	[0.3235]
q-value	[0.2327]	[0.3235]
Controls	No	Yes
Sample Size	1,333	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses. P-values are shown for each estimate in brackets in the row titled “p-values”. Adjusted q-values from the Simes procedure to correct for multiple hypothesis testing are for each estimate in brackets in the row titled “q-values”. Registration refers to appearing in the voter registration rolls of the corresponding location, which requires American citizenship and covers roughly three quarters of all American citizens. “Baseline” refers to the mean value of the outcome variable for the smallest tuition waiver treatment arm (\$20,000).

Table 3: Labor Mobility Effects of Nonresident Tuition Waivers per 10,000 Dollars

Outcome	(1)	(2)
<i>A. Labor Supply in Target State 12 Years Later (N=397)</i>		
	<i>[Baseline: 0.0909]</i>	
Executives in Target State	0.0591** (0.0236)	0.0688*** (0.0237)
p-value	[0.0127]	[0.0040]
q-value	[0.0339]	[0.0161]
	<i>[Baseline: 0.0070]</i>	
Entrepreneurs in Target State	0.0089 (0.0082)	0.0071 (0.0075)
p-value	[0.2788]	[0.3440]
q-value	[0.3187]	[0.3440]
	<i>[Baseline: 0.1119]</i>	
Innovators in Target State	0.0517** (0.0246)	0.0564** (0.0247)
p-value	[0.0367]	[0.0230]
q-value	[0.0534]	[0.0460]
<i>B. NPV of Earnings in the Target State (N=1,333)</i>		
	<i>[Baseline: \$80,218]</i>	
Salary in Target State	34151*** (11718)	25302** (12314)
p-value	[0.0036]	[0.0401]
q-value	[0.0161]	[0.0534]
Controls	No	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses. P-values are shown for each estimate in brackets in the row title “p-values”. Adjusted q-values from the Simes procedure to correct for multiple hypothesis testing are for each estimate in brackets in the row titled “q-values”. Executives refers to an indicator for both residing in-state and being flagged as having executive leadership skills given pre-specified definitions based on their employment history and profiles on LinkedIn. Entrepreneurs refers to an indicator for both residing in-state and being flagged as having entrepreneurial skills given pre-specified definitions based on their employment history and profiles on LinkedIn. Innovators refers to an indicator for both residing in-state and being flagged as having research or innovation skills given pre-specified definitions based on their employment history and profiles on LinkedIn. Salary refers to an indicator for residing in-state interacted with estimated taxable earnings from Revelio Labs using job titles, work history, and employer, with imputed values for missing observations following this paper’s pre-analysis plan. “Baseline” refers to the mean value of the outcome variable for the smallest tuition waiver treatment arm (\$20,000).

Table 4: Labor Mobility Effects of Nonresident Tuition Waivers per 10,000 Dollars

Outcome	(1)	(2)
<i>A. Labor Supply in the US 12 Years Later (N=397)</i>		
	<i>[Baseline: 0.4755]</i>	
Executives in United States	-0.0494 (0.0335)	-0.0474 (0.0326)
p-value	[0.1414]	[0.1476]
q-value	[0.5904]	[0.5904]
	<i>[Baseline: 0.0629]</i>	
Entrepreneurs in United States	0.0023 (0.0168)	-0.0012 (0.0169)
p-value	[0.8905]	[0.9455]
q-value	[0.9455]	[0.9455]
	<i>[Baseline: 0.4825]</i>	
Innovators in United States	-0.0067 (0.0339)	-0.0066 (0.0327)
p-value	[0.8433]	[0.8407]
q-value	[0.9455]	[0.9455]
<i>B. NPV of Earnings in the United States (N=1,333)</i>		
	<i>[Baseline: \$167,787]</i>	
Salary in United States	14643 (13940)	9016 (11909)
p-value	[0.2936]	[0.4491]
q-value	[0.7831]	[0.8982]
Controls	No	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses. P-values are shown for each estimate in brackets in the row titled “p-values”. Adjusted q-values from the Simes procedure to correct for multiple hypothesis testing are for each estimate in brackets in the row titled “q-values”. Executives refers to an indicator for both residing in the United States and being flagged as having executive leadership skills given pre-specified definitions based on their employment history and profiles on LinkedIn. Entrepreneurs refers to an indicator for both residing in the United States and being flagged as having entrepreneurial skills given pre-specified definitions based on their employment history and profiles on LinkedIn. Innovators refers to an indicator for both residing in the United States and being flagged as having research or innovation skills given pre-specified definitions based on their employment history and profiles on LinkedIn. Salary refers to an indicator for residing in the United States interacted with estimated taxable earnings from Revelio Labs using job titles, work history, and employer, with imputed values for missing observations following this paper’s pre-analysis plan. “Baseline” refers to the mean value of the outcome variable for the smallest tuition waiver treatment arm (\$20,000).

Online Appendices

A Pre-Analysis Plan Appendix

A.1 Summary Statistics

The variables included in this project are (1) an indicator for being raised by a single parent, (2) a head count of a student's household size, (3) an indicator for no data on household size, (4) self-reported family income, (5) an indicator for having reported family income, (6) an indicator for being a first generation college student, (7) estimated age at college entry, (8) an indicator for no age data, (9) a student's best SAT or ACT equivalent score, (10) an indicator for no standardized test score, (11) a student's weighted high school GPA, (12) a student's overall admission score, (13) a financial aid application indicator, (14) an indicator for honors admission, (15) an indicator for receiving a separate merit scholarship offer, (16) an indicator for self-identifying as female, (17) a categorical variable for father's education, (18) a categorical variable for mother's education, (19) a categorical variable for the school/department of the major the student listed as their first preference, (20) a categorical variable for home country or region of a student's mailing address, (21) an overall academic rating of the student from the research university, (22) a holistic score, (23) a student's expected family contribution (EFC) value, (24) an indicator for no EFC data, and (25) a categorical variable for ethnic identity.¹⁴ After completion of the project, the target university was able to provide records of students' American citizenship and permanent residency at the time of college application.¹⁵

¹⁴In the pre-analysis plan, I had pre-registered that variable number 11 was an unweighted GPA, but the target university instead provided weighted GPA. Variable 13 was intended to be an indicator for having filed a Free Application for Federal Student Aid (FAFSA), but the target university instead provided an indicator for applying for any form of financial aid.

¹⁵When the pre-analysis plan for the project was submitted, the target university had been using a noisy indicator it had retained for American citizenship. That indicator was not included in the PAP because of concerns about accuracy. After the project was completed, the target university discovered an another set of records for students in the 2011-2012 application cycle with detailed records on citizenship and provided an indicator of American citizenship or residency. Because this was not a pre-registered variable, I denote each place in the manuscript where the variable is used.

Table A.1: Full Sample Summary Statistics

	Mean	Min	Max
Raised by Single Parent	.1222806	0	1
Household Size	3.762191	2	12
No Household Size	.0705176	0	1
Family Income	194196	0	999999
No Income Report	.1327832	0	1
First Generation	.1965491	0	1
Age at Entry	18.80683	16.35089	22.07042
No Age Data	.0157539	0	1
Best SAT/ACT	1850.048	1040	2400
No SAT Score	.0255064	0	1
GPA	3.866174	1.72	4.38
Admission Score	244.4756	164	300
Financial Aid Application	.2348087	0	1
Honors Student	.0435109	0	1
Merit Scholarship	.012003	0	1
Female	.5536384	0	1
Expect Family Contribution	22371.02	0	99999
Origin: Americas	.0270068	0	1
Origin: China	.4553638	0	1
Origin: Europe or Africa	.0067517	0	1
Origin: Korea	.0802701	0	1
Origin: Other Asia or Oceania	.0892723	0	1
Origin: US, Same Region	.2370593	0	1
Origin: US, Other Region	.1042761	0	1

Note: Family income and expected family contribution are measured in dollars and are top-coded at values of 999,999 dollars per year and 99,999 dollars respectively. These values represent students with family incomes and expected family contributions above the respective ceilings rather than students with missing data.

A.2 Pre-specified Balance Tests

Table A.2: Association between Tuition Waiver Size and Pre-Treatment Demographics

Outcome	(1)
Raised by Single Parent	0.0113 (0.0120)
Household Size	-0.0149 (0.0386)
No Household Size Data	-0.0064 (0.0093)
Reported Family Income	-1.80e+04** (7398.2816)
No Reported Income	0.0113 (0.0130)
First Generation Student	-0.0218 (0.0149)
Age at College Entry	0.0297 (0.0242)
No Age Reported	-0.0000 (0.0040)
Best SAT Score	0.4631 (8.1583)
No SAT Score	0.0050 (0.0056)
Sample Size	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table A.3: Association between Tuition Waiver Size and Pre-Treatment Demographics

Outcome	(1)
Weighted GPA	0.0099 (0.0089)
Admission Score	-0.0463 (0.8269)
FAFSA Indicator	-0.0028 (0.0157)
Honors Student	0.0050 (0.0075)
Merit Scholarship	-0.0013 (0.0042)
Female	0.0056 (0.0188)
Sample Size	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table A.4: Association between Tuition Waiver Size and Pre-Treatment Demographics

Outcome	(1)
dad==2-Year College Graduate	-0.0115 (0.0083)
dad==4-Year College Graduate	0.0021 (0.0184)
dad==High School Graduate	0.0088 (0.0100)
dad==NULL	-0.0090 (0.0086)
dad==No High School	-0.0051 (0.0047)
dad==Postgraduate Study	0.0148 (0.0177)
dad==Some College	0.0037 (0.0097)
dad==Some High School	-0.0038 (0.0060)
Sample Size	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table A.5: Association between Tuition Waiver Size and Pre-Treatment Demographics

Outcome	(1)
mom==2-Year College Graduate	0.0075 (0.0105)
mom==4-Year College Graduate	-0.0005 (0.0187)
mom==High School Graduate	0.0011 (0.0124)
mom==NULL	-0.0026 (0.0086)
mom==No High School	-0.0064 (0.0052)
mom==Postgraduate Study	0.0175 (0.0151)
mom==Some College	-0.0064 (0.0107)
mom==Some High School	-0.0102* (0.0053)
Sample Size	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table A.6: Association between Tuition Waiver Size and Pre-Treatment Demographics

Outcome	(1)
major==Interdisciplinary	0.0013 (0.0022)
major==None	0.0263 (0.0160)
major==Life Science	-0.0090 (0.0118)
major==Arts	0.0012 (0.0065)
major==Humanities	0.0025 (0.0078)
major==Physical Science	-0.0116 (0.0118)
major==Social Science	-0.0244 (0.0151)
major==Engineering	0.0151 (0.0124)
major==Management Science	-0.0001 (0.0087)
major==Nursing Science	-0.0013 (0.0013)
major==Pharmacy Science	-0.0026 (0.0044)
major==Computer Science	-0.0051 (0.0079)
major==Public Health	0.0025 (0.0031)
major==Other	0.0050 (0.0059)
Sample Size	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table A.7: Association between Tuition Waiver Size and Pre-Treatment Demographics

Outcome	(1)
home==Americas	-0.0038 (0.0065)
home==China	-0.0057 (0.0189)
home==Europe or Africa	-0.0013 (0.0028)
home==Korea	-0.0039 (0.0100)
home==Other Asia or Oceania	0.0050 (0.0111)
home==US - Far	0.0010 (0.0159)
home==US - Near	0.0087 (0.0116)
Sample Size	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table A.8: Association between Tuition Waiver Size and Pre-Treatment Demographics

Outcome	(1)
ethnic==African-American or Black	-0.0076 (0.0047)
ethnic==American Indian	-0.0013 (0.0013)
ethnic==Caucasian or White	0.0252* (0.0129)
ethnic==Chicano/Mexican-American	0.0025 (0.0044)
ethnic==Chinese/Chinese-American	-0.0083 (0.0189)
ethnic==Declined To State	-0.0013 (0.0072)
ethnic==East Indian/Pakistani	-0.0013 (0.0078)
ethnic==Japanese/Japanese-American	-0.0000 (0.0044)
ethnic==Korean	-0.0065 (0.0129)
ethnic==Latino/Oth Span-American	0.0012 (0.0049)
ethnic==Other Asian	-0.0064 (0.0052)
ethnic==Philipino or Filipino	0.0012 (0.0058)
ethnic==Polynesian	-0.0025 (0.0018)
ethnic==Vietnamese	0.0051 (0.0050)
Sample Size	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table A.9: Association between Tuition Waiver Size and Predicted Outcomes

Outcome	(1)
<i>A. Enrollment</i>	
Target University	-0.0008 (0.0084)
Any Target State College	-0.0001 (0.0068)
Any US College	0.0053 (0.0066)
<i>B. Migration</i>	
Registered in Target State	0.0077* (0.0045)
Registered in United States	0.0100 (0.0110)
<i>C. Target State Labor Market</i>	
Executives in Target State	0.0003 (0.0012)
Innovators in Target State	0.0006 (0.0013)
Entrepreneurs in Target State	0.0003 (0.0005)
Salary in Target State	1.04e+04** (4653.0823)
<i>D. US Labor Market</i>	
Executives in United States	-0.0011 (0.0021)
Innovators in United States	-0.0001 (0.0020)
Entrepreneurs in United States	0.0003 (0.0009)
Salary in United States	6196.4450 (9606.4742)
Sample Size	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

A.3 Deviations from the Pre-Analysis Plan

I note the following deviations from the pre-analysis plan:

- I did not receive data on medium-run outcomes like college graduation and academic performance. Hence, these outcomes were not examined in the manuscript.
- Some variables had somewhat different definitions than was initially anticipated. For example, I received weighted rather than unweighted GPA. These differences are noted in Section 3.1 of the paper.
- I received a variable that was not pre-registered: a binary indicator for American citizenship or residency at the time of college application. I note that this variable was not included in the PAP each time I reference a result including it in the manuscript.
- Estimates are per 10,000 dollars of nonresident tuition rather than per 1,000 dollars to make results more easily interpretable.
- The assumed state-level tax rate on earnings was reduced from 25 percent to 5 percent in Section 5. The 25 percent rate in the PAP was intended to reflect the rough rate of federal tax revenue as a share of GDP, but was inadvertently also listed at the state level. In most American states, tax revenue is roughly 5 percent of Gross State Product. This switch makes my results more conservative.
- Specifications that look at each treatment arm separately were suggested by a referee.
- Estimates of effects on college enrollment decomposed by sector was suggested by a referee.

A.4 Pre-specified Variable Definitions

This paper uses the following definitions for labor market outcomes that rely on Revelio Labs' records on the universe of LinkedIn profiles:

- **LinkedIn Location:** This is defined as the metropolitan area listed on LinkedIn profiles. This variable is set to the country listed on the profile if the metropolitan area is missing. These data come from Revelio Labs and manually collected LinkedIn records.
- **LinkedIn Earnings:** This is defined as the imputed earnings based on work history and job title from Revelio Labs dataset. In cases where this is absent, we will link job titles to the most similar BLS occupation code and its annual mean wages. These data will come from Revelio Labs and manually collected records. I assume students work for 20 years at a constant level of earnings in their recorded place of residence beginning 8 years after college application to be conservative. Earnings will be imputed for people without LinkedIn job titles by assuming an annual mean earnings level equal to the sample average estimated mean annual wage for students whose occupational titles are observed.
- **LinkedIn Entrepreneurship:** This is defined as having a relevant term in **any** part of the LinkedIn profile. The relevant terms are: Entrepreneur, Founder, Co-founder, Creator, Startup, Owner, CEO, Venture, Investor, or Strategist.
- **LinkedIn Innovation:** This is defined as having a relevant term in **any** part of the LinkedIn profile. The relevant terms are: Inventor, Patent, Innovation, Innovator, Developer, Development, Research, Scientist, Engineer, Technology/Technologist, Design, Data, Idea, or Lab/Laboratory.
- **LinkedIn Executive Experience:** This is defined as having a relevant term in **any** part of the LinkedIn profile. The relevant terms are: Chief, Officer, President, Director, Board, Executive, Chair/Chairman, Manager/Management/Managing, Partner, Head, Lead, or Senior.

B Extensions

B.1 Decomposition of Enrollment by Sector

Table B.1: Enrollment Effects of Nonresident Tuition Waivers per 10,000 Dollars

Outcome	(1)	(2)
<i>A. Enrollment by Institution Types</i>		
No US College	-0.0156 (0.0175)	-0.0110 (0.0173)
Non-AAU US Campus	-0.0103 (0.0116)	-0.0149 (0.0108)
Public AAU Campus	0.0374** (0.0189)	0.0411** (0.0190)
Private AAU Campus	-0.0115 (0.0096)	-0.0152 (0.0097)
Controls	No	Yes
Sample Size	1,333	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

B.2 Estimates by Treatment Arm

While the primary analysis estimates treatment effects linearly across waiver size, disaggregating the effects by treatment arm reveals meaningful heterogeneity that informs both mechanism and external validity. Tables X through Z report separate estimates for the 20,000 dollar, 30,000 dollar, and 40,000 dollar treatment arms.

Table B.2 presents short-run enrollment outcomes. Effects on enrollment at the target university and other institutions within the state are larger when comparing the 30,000 dollar and 40,000 dollar arms than when comparing the 20,000 dollar and 30,000 dollar arms. This pattern suggests a convex demand curve, with student enrollment more responsive on a per-dollar basis at lower net prices. In contrast, when examining enrollment at any college or university within the United States, the effects are larger between the 20,000 dollar and 30,000 dollar treatment arms, with negligible or even negative effects from increasing the waiver from 30,000 dollars to 40,000 dollars. This could reflect differences in students' counterfactual options at higher willingness to pay levels or behavioral effects of large tu-

ition discounts altering students' perceptions of campus quality (e.g., Veblen effects). The correspondence of these patterns with later residence outcomes reduces the likelihood that they are attributable solely to estimation noise.

Table B.3 presents effects on long-run in-state residence. Migration to the target state increases with the size of the waiver, but while the 40,000 dollar treatment arm yields the largest effect in magnitude, the marginal gain from 30,000 to 40,000 dollars is smaller than the gain from 20,000 to 30,000 dollars, suggesting possible diminishing returns. Residence anywhere in the United States follows an identical pattern to college enrollment in the United States twelve years earlier, again suggesting that students on the margin of migrating to the United States have a much higher willingness to pay.

Tables B.4 and B.5 report effects on labor market outcomes in the target state and the United States as a whole. The largest increases in executive and innovator migration to the target states occur in the 30,000 dollar treatment arm, with smaller, but still statistically significant, effects at 40,000 dollars. These patterns are consistent with concave externalities: the students most likely to generate long-run labor market spillovers appear to be those with relatively high willingness to pay and are most responsive at intermediate levels of tuition relief. Across all treatment arms, labor market outcomes in the United States remain null, consistent with the results from the linear specification.

Table B.6 presents results for the net present value of labor market earnings. In the target state, the increase in long-run earnings is substantially larger for students in the 30,000 dollar treatment arm than for those in the 40,000 dollar arm, despite both being statistically significant. This again points to diminishing marginal returns and suggests that the long-run externalities are driven more by the retention of students already inclined to enroll than by expansion at the margin. While the linear specification showed no significant earnings gains in the United States overall, disaggregating by treatment arm reveals that the 30,000 dollar group does exhibit meaningful increases in national labor market earnings. These patterns align closely with earlier results for U.S. college enrollment and migration, reinforcing the idea that the students on the margin of remaining in the U.S. labor market have particularly high willingness to pay.

Taken together, these results suggest that the long-run effects of tuition waivers on migration and fiscal externalities are not simply a function of increased enrollment. Instead, they appear to operate through the retention of students who would have enrolled regardless but might otherwise have left the state after graduation. The results also imply that moving from no waiver to a 20,000 dollar waiver would likely generate even larger returns on a per-dollar basis than those observed in the experimental arms. By contrast, additional waivers beyond 30,000 dollars exhibit diminishing or flat marginal returns. These patterns point

to the existence of an optimal level of nonresident supplemental tuition that maximizes the net public benefit from skilled migration while minimizing the institutional cost of foregone tuition revenue.

Table B.2: Enrollment Effects of Nonresident Tuition Waivers by Treatment Arm

	(1)	(2)	(3)	(4)	(5)	(6)
	Target U	Target U	State	State	USA	USA
30,000 Dollars	0.0180 (0.0253)	0.0289 (0.0216)	0.0315 (0.0333)	0.0429 (0.0324)	0.0563* (0.0306)	0.0457 (0.0299)
40,000 Dollars	0.0558** (0.0263)	0.0611*** (0.0229)	0.0867*** (0.0333)	0.0927*** (0.0335)	0.0277 (0.0310)	0.0198 (0.0307)
Controls	No	Yes	No	Yes	No	Yes
Sample Size	1,333	1,333	1,333	1,333	1,333	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table B.3: Migration Effects of Nonresident Tuition Waivers by Treatment Arm

	(1) State	(2) State	(3) USA	(4) USA
30,000 Dollars	0.0450** (0.0185)	0.0317* (0.0182)	0.0653** (0.0283)	0.0384* (0.0218)
40,000 Dollars	0.0583*** (0.0191)	0.0477** (0.0187)	0.0378 (0.0278)	0.0216 (0.0217)
Controls	No	Yes	No	Yes
Sample Size	1,333	1,333	1,333	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table B.4: Effect on Target State Migration of Nonresident Tuition Waivers by Arm

	(1)	(2)	(3)	(4)	(5)	(6)
	Executive	Excutive	Entrepreneur	Entrepreneur	Innovator	Innovator
30,000 Dollars	0.1341*** (0.0452)	0.1687*** (0.0487)	0.0263 (0.0179)	0.0276 (0.0196)	0.1464*** (0.0481)	0.1725*** (0.0531)
40,000 Dollars	0.1031** (0.0419)	0.1175*** (0.0423)	0.0154 (0.0146)	0.0118 (0.0135)	0.0896** (0.0437)	0.0950** (0.0437)
Controls	No	Yes	No	Yes	No	Yes
Sample Size	1,333	1,333	1,333	1,333	1,333	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table B.5: Effect on United States Migration of Nonresident Tuition Waivers by Arm

	(1)	(2)	(3)	(4)	(5)	(6)
	Executive	Excutive	Entrepreneur	Entrepreneur	Innovator	Innovator
30,000 Dollars	-0.0505 (0.0617)	-0.0309 (0.0586)	-0.0046 (0.0296)	0.0014 (0.0327)	0.0175 (0.0621)	0.0463 (0.0618)
40,000 Dollars	-0.0875 (0.0595)	-0.0844 (0.0581)	0.0042 (0.0298)	-0.0021 (0.0298)	-0.0124 (0.0603)	-0.0138 (0.0582)
Controls	No	Yes	No	Yes	No	Yes
Sample Size	1,333	1,333	1,333	1,333	1,333	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table B.6: Labor Mobility Effects of Nonresident Tuition Waivers by Treatment Arm

	(1) Profit	(2) Profit	(3) State	(4) State	(5) USA	(6) USA
30,000 Dollars	-827.72 (970.27)	-400.27 (818.07)	85092.25*** (24867.37)	72641.24*** (24328.56)	65446.29** (26334.43)	44041.75** (21607.69)
40,000 Dollars	-1480.80* (893.89)	-1264.00 (777.16)	60590.59*** (20744.35)	45267.44** (21775.59)	26001.31 (24695.45)	16277.31 (21125.85)
Controls	No	Yes	No	Yes	No	Yes
Sample Size	1,333	1,333	1,333	1,333	1,333	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

C Heterogeneous Treatment Effects

Heterogeneous treatment effects are tested along two pre-specified dimensions: country of home address and STEM major intent at the time of college application. I begin by generating tables with identical outcomes and specifications to Table D.1 that estimate effects separately for (1) all nonresident students with a primary home address in China, Taiwan, or Hong Kong in Table C.1. These students are close to half the full sample (45 percent). Next, I turn to all nonresident students with a primary home address outside of the United States (66 percent of the sample) in Table C.2, and all nonresident students with a primary home address in the United States (33 percent of the sample) in Table C.3. I caution that primary home address in this case does not align perfectly with citizenship nor with domestic out-of-state or foreign student status.

Across these tables I note that point estimates suggest more mobility between states for nonresident students with a domestic home address and more mobility between countries for nonresidents with an international address, especially among students with a home address in China. However, given that I cannot reject the null hypothesis that these results are the same across groups, I interpret these findings to imply that my results are relatively similar regardless of a student’s place of origin.¹⁶

With regard to STEM major intent, I split the sample into STEM and non-STEM major groups based on whether their first preference major at the research university is a CIP-designated STEM major by the US Department of Homeland Security. This is a useful measure of STEM status because the ease of immigration and labor market participation laws in the United States is relaxed for students completing a CIP designated STEM major (Amuedo-Dorantes et al., 2020; Beine et al., 2023).

Results are shown for STEM students in Table C.4 and Non-STEM students in Table C.5. Consistent with the theoretical prediction that STEM students are more mobile because of the greater ease of immigration under US law and consistent with higher expected earnings for STEM workers, results are stronger among students with STEM major intent. Every 10,000 dollars in tuition waiver offers to students intending to major in STEM costs the target university 760 dollars in short-run profit but returns 59,800 dollars in discounted earnings to the state in which the target university resides. This finding suggest that streamlining immigration laws and reducing nonresident tuition can be complementary policies. Places seeking to attract skilled workers can reduce both the financial and bureacratic barriers

¹⁶In a test of heterogeneous treatment effects that uses a variable that was not anticipated and included in the PAP, I find that there are significantly (t-statistic 2.31) larger effects on earnings within the target state’s labor market from students who were citizens or American legal permanent residents at the time of college application.

to immigration simultaneously, raising longer-run migration at comparatively low short-run costs.

Table C.1: Effects of Tuition Waivers per 10,000 Dollars among Chinese Residents

Outcome	(1)	(2)
<i>A. NPV of Profit for Target University</i>		
NPV of Profit	-1724** (811)	-1996*** (726)
<i>B. NPV of Earnings in the Target State</i>		
Salary in Target State	24155 (15839)	30938* (17448)
<i>C. NPV of Earnings in the United States</i>		
Salary in United States	15964 (10901)	28969** (12508)
Controls	No	Yes
Sample Size	607	607

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table C.2: Effects of Tuition Waivers per 10,000 Dollars among International Nonresidents

Outcome	(1)	(2)
<i>A. NPV of Profit for Target University</i>		
NPV of Profit	-1212* (653)	-1222** (564)
<i>B. NPV of Earnings in the Target State</i>		
Salary in Target State	17543 (13044)	14847 (13961)
<i>C. NPV of Earnings in the United States</i>		
Salary in United States	13824 (9183)	20242** (9821)
Controls	No	Yes
Sample Size	878	878

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table C.3: Effects of Tuition Waivers per 10,000 Dollars among Domestic Nonresidents

Outcome	(1)	(2)
<i>A. NPV of Profit for Target University</i>		
NPV of Profit	7 (748)	346 (735)
<i>B. NPV of Earnings in the Target State</i>		
Salary in Target State	63207*** (22887)	36070 (26959)
<i>C. NPV of Earnings in the United States</i>		
Salary in United States	3154 (30451)	-15866 (33480)
Controls	No	Yes
Sample Size	455	455

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table C.4: Effects of Tuition Waivers per 10,000 Dollars among STEM Majors

Outcome	(1)	(2)
<i>A. NPV of Profit for Target University</i>		
NPV of Profit	-762 (747)	-545 (648)
<i>B. NPV of Earnings in the Target State</i>		
Salary in Target State	59795*** (20429)	40739* (23485)
<i>C. NPV of Earnings in the United States</i>		
Salary in United States	28421 (24719)	19378 (22854)
Controls	No	Yes
Sample Size	540	540

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

Table C.5: Effects of Tuition Waivers per 10,000 Dollars among Non-STEM Majors

Outcome	(1)	(2)
<i>A. NPV of Profit for Target University</i>		
NPV of Profit	-935 (678)	-1110* (604)
<i>B. NPV of Earnings in the Target State</i>		
Salary in Target State	17717 (13983)	18135 (14939)
<i>C. NPV of Earnings in the United States</i>		
Salary in United States	7228 (16125)	10039 (13437)
Controls	No	Yes
Sample Size	793	793

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses.

D Short-run and Long-run Trade-offs

Table D.1: Effects of Nonresident Tuition Waivers per 10,000 Dollars

Outcome	(1)	(2)
<i>A. NPV of Profit for Target University</i>		
NPV of Profit	-835*	-714
	(504)	(438)
<i>B. NPV of Earnings in the Target State</i>		
Salary in Target State	34151***	25302**
	(11718)	(12314)
<i>C. NPV of Earnings in the United States</i>		
Salary in United States	14643	9016
	(13940)	(11909)
Controls	No	Yes
Sample Size	1,333	1,333

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity robust standard errors in parentheses. Profit refers to the difference between net tuition paid by the student and estimated instructional expenditures. Salary refers refers to an indicator for location interacted with estimated taxable earnings from Revelio Labs using job titles, work history, and employer, with imputed values for missing observations following this paper's pre-analysis plan. All values are discounted at a 5 percent annual rate consistent with this paper's pre-analysis plan.