Predicting International Student Enrollment by Institutional Aid: A Random and Fixed Effects Approach

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Since the fall semester of 2016, first-time international student enrollment (ISE_{ft}) has declined at U.S. colleges and universities. This trend disrupts a steady upwards trajectory of ISE_{ft} rates. Previous research has demonstrated that various political, social, and macroeconomic factors influence the number of international students studying in the U.S. Exploiting data from the Common Data Set (CDS), I focus on the role financial aid plays as an enrollment predictor for international undergraduate students. A fixed effects model reveals that financial aid is strongly and significantly predictive of ISE_{ft}, yielding a 1.8% enrollment increase per 10% aid increase, all else equal. Interestingly, financial aid is only predictive of ISE_{ft} if it is awarded in substantial amounts. Extending the work of Bicak and Taylor (2020), I also analyze how the effectiveness of financial aid awards varies within different institutional settings. Random effects regressions reveal that rural, low research, and private universities experience considerable marginal ISE_{ft} boosts when awarding aid to international students. The findings of this work are primarily directed at institutional leaders who seek to revitalize their institution's ISE_{ft} policy. Moreover, these insights may inform local policymakers who seek to incent ISE_{ft}.

Keywords: *international student enrollment, financial aid, panel data regression, treatment effect heterogeneity*

Since the fall semester of 2016[1] (Institute of International Education (IIE), 2021), first-time international student enrollment (ISE_{ft}) has steadily declined at U.S. universities[2]. Described as the "Trump Effect," Hacker and Bellmore (2020) claim that factors like anti-immigration rhetoric, administrative hurdles, and personal safety threats induced a sudden ISE_{ft} decline. Moreover, Shih (2016) argues that an increasingly challenging job market has made studying in the U.S. less attractive to international students. Finding that work visa issuances per country are positively and significantly related to the number of international students from that country, Shih illustrates that international students rely on career outlooks to justify the expensive decision to study abroad.

While various policy angles may offer an answer to this question, this paper approaches the issue from the institutional perspective. Institutions leverage a wide array of tools to incentivize enrollment for certain student groups. One of the most well-known and popular tools is subsidizing a student's cost of attendance by awarding financial aid through grants, scholarships, or other direct payments (Leslie & Brinkman, 1987; Heller, 1997). Universities use aid to control student body size, diversity, and composition. Often, they employ this tactic to attract domestic students with certain characteristics, such as a certain nationality, socioeconomic background, or race. A common example are universities with distinct minority-focused scholarship programs.[3]

Motivated by the recent decline in ISE_{ft}, this paper's goal is to provide a detailed analysis of the relationship between financial aid and ISE_{ft}. Since nonresident aliens are ineligible for state and federal aid programs, this study looks at institutional sources of aid.[4] Using exclusive data from the Common Data Set (CDS), I address the lack of literature on ISE_{ft} determinants, specifically financial

[1]See Appendix A.

[2]The author uses the terms college, institution, school, and university interchangeably.

[3]For example, the Turner Scholars program at the University of Cincinnati.

[4]The author uses the terms institutional aid and financial aid interchangeably.

aid. My findings serve as guidance to institutional decision-makers and local policymakers. Understanding how aid relates to enrollment may revitalize international student aid policies in the aftermath of COVID-19.

I organize the remainder of the paper as follows: First, I describe the institutional setting, existing literature, the data, and the sampling strategy. The next section addresses interpretation and challenges associated with a causal inference framework. The following section introduces the empirical strategy, presenting the results for both the fixed effects and random effects models, and addressing the limitations of this study. The final sections conclude with a discussion and an overview of implications for policy and practice.

Institutional Setting

Previous literature examines the relationship between financial aid and ISE_{ft} but is limited in scope. Bound et al. (2020) are limited to public institutions, Zhang and Hagedorn (2018) to community colleges, and Curs and Jaquette (2017) failed to distinguish between out-of-state and international applicants. Moreover, there is a wealth of literature examining the relationship of financial and domestic student enrollment. Dynarski (2000) showed that the Georgia-based HOPE scholarship raised the probability of college attendance for 18–19-year-old Georgian residents by about 25%. Cornwell et al. (2006) complemented this insight by asserting that HOPE also raised total first-time freshman enrollment. In addition to merit-based aid, domestic students are eligible for need-based federal aid, such as the Pell Grant. Further evidence supports that need-based financial aid has a significant effect on enrollment (Dynarski, 2003; Kane, 1999; Leslie & Brinkman, 1987; Seftor & Turner, 2002).

Bicak and Taylor (2020) tied these advances into a broad analysis of ISE_{ft} predictors. Albeit only considering fixed institutional characteristics (e.g., location and research intensity), Bicak and Taylor considered a wide variety and combination of ISE_{ft} predictors. Leveraging data from the Integrated Postsecondary Education Data System (IPEDS) administered by the National Center for Education Statistics (NCES), Bicak and Taylor found that certain institutional characteristics significantly predict ISE_{ft}, e.g., average institutional grant aid to first-time undergraduate students at low research activity institutions.[5] Bicak and Taylor also found that less research-intensive institutions have adapted in the higher education industry by incenting ISE_{ft} through institutional grant aid. While Bicak and Taylor concluded that many of the strongest predictors of ISE_{ft} are fixed/time-invariant, their findings raise the question on how potent of an enrollment incentive financial aid is for international students. The Bicak and Taylor study constitutes an important node between the various strands of financial aid literature and this study's goal: A comprehensive assessment of ISE_{ft} predictors.

A complication concerning this study's scope is constituted by the nature of financial aid awards. Financial aid offers are largely determined by individual characteristics, e.g., ability (Van Der Klaauw, 2002), that cannot be observed in the CDS data. This is emblematic of international student data, where the only potential source for such information is confidential immigration data. Therefore, it is important to emphasize that this study examines financial aid as a predictor from the institutional lens. Rather than examining the effect of financial aid on an individual student's enrollment decision, I focus on the correlation between a university's total change in financial aid awards and the total change in ISE_{ft}. This shift of scope voids the need for individual data, seeing

[5] Bicak and Taylor use the Carnegie classification to distinguish between low ('Bachelor'), medium ('Masters'), and high ('Doctoral') research activity institutions.

that an institutional aid award can now be analyzed as an aggregate award per incoming freshman class per academic year.

Determinants of International Student Enrollment

What influences ISE_{ft}? Macroeconomic factors, e.g., labor market openness regulated through work visa (H1-B) issuances to a country *i* at time *t*, affect the number of international students choosing to study abroad (Shih, 2016). Additionally, in accordance with Bicak and Taylor (2020), it is institutional factors that are most influential in determining ISE_{ft}. Therefore, determining the predictors of ISE_{ft} necessitates a robust specification of confounding variables, as well as institution- and time-specific factors.

Determinants of student enrollment can be split up into two general categories. First, time-invariant determinants are fixed institutional characteristics that influence student enrollment. These characteristics can either not be changed by the institutions or can only be altered over a long time. Bicak and Taylor (2020) summarize and evaluate the importance of a broad set of time-invariant institutional characteristics in their work. Most notably, Bicak and Taylor conclude that factors like level of research intensity, location, size, and various investments (e.g., expenses on student services, instructional expenses while considering the institution's fixedness) are strongly predictive of ISE_{ft}. Bicak and Taylor make particular mention of the critical role of geography, a detail I address when interpreting the random effects models.

Second, time-variant determinants of student enrollment are controllable by an institution. Previous literature offers abundant insight into the importance of certain predictors, including financial aid (Beine et al., 2014; Cantwell, 2019; Cornwell et al., 2006; Dynarski, 2000, 2003; Li, 2017). It is noteworthy that most of this literature distinguishes between place-based, merit-based, and need-based aid. CDS data infrequently included this information, barring me from considering different types of financial aid. I discuss controls in the variables of interest section.

While certain determinants – e.g., geography – are predictive of both domestic and international student enrollment (Bicak & Taylor, 2020; Cantwell, 2019), domestic and international student enrollment are not driven by the same factors. Van Der Klaauw (2002) highlights that non-U.S. citizens exhibit significantly lower enrollment elasticity than their U.S. counterparts. As it relates to financial aid, this means that international students could - all else equal - be more sensitive to financial support given their ineligibility in state and federal level aid programs. Moreover, it could be indicative of international students requiring more substantial amounts of aid than their domestic counterparts due to higher costs, e.g., travel and relocation. The specification of the fixed effects model pays particular attention to the cost barrier.

Addressing Heterogeneity in Higher Education

Higher education institutions (HEI) exist in every U.S. state. Comparing them with each other raises the problem of geographical heterogeneity. To avoid comparing institutions across important geographical predictors of enrollment, this study's scope is limited to a single region within the United States: The Great Lakes region.[6] The five states – Ohio, Indiana, Illinois, Michigan, and Wisconsin – exhibit similar geographic characteristics. This helps minimize location-specific

[6]Note that the choice of this region itself is arbitrary. This limitation should motivate future research to extend this work to other U.S. regions.

enrollment biases such as inherently attractive geographic characteristics (e.g., the warm California weather). Additionally, time constraints limited my ability to aggregate data from multiple regions.

An additional problem plaguing higher education research is that institutions themselves are structurally different. For small universities, an enrollment increase of 100 students is more meaningful than for a large university. To address this issue, I standardize all financial and enrollment variables through a logarithmic transformations. This enables me to interpret my results as percentage changes rather than absolute values. Additionally, the log-log framework addresses the skewness of the variables and allows for an intuitive interpretation. Log-log standardization has been successfully employed in studies such as Mincer (1974); Card (1999); as well as Bicak and Taylor (2020). All financial variables are converted to 2020 dollars using the Commonfund Institute's (2018) Higher Education Price Index (HEPI).

Data

This study exclusively considers undergraduate students. I limit my analysis to 4-year institutions due to the structural differences at 2-year colleges, where different motivations – like transitioning opportunities – primarily drive ISE_{ft} (Zhang & Hagedorn, 2018).

There is a total of 444 4-year, Title-IX universities in the Great Lakes region. I exclude for-profit institutions as there are not enough for meaningful analysis. Moreover, I exclude all special-interest colleges, such as bible colleges and seminary schools. It is important to note, however, that a university with a religious affiliation does not automatically qualify as a special-interest school. Only schools that advertise their special interest as their defining attribute are classified as such. Since I am interested in aid variation over time, I only consider universities that award non-zero aid to international students in at least two academic years. Moreover, I exclude universities that enroll less than ten international students per year.[7] This helps me capture meaningful variations in both ISE_{ft} and financial aid over time.[8] After these additional restrictions, 386 universities qualify for analysis in the region.

The data for the control variables[9] are gathered from the Integrated Postsecondary Education Data System (IPEDS) database. Unfortunately, IPEDS does not give insight into international student aid data. That is why I leveraged the availability of CDS data. The CDS is a collaborative and standardized effort to improve the quality and accuracy of higher education information.[10] Notably, CDS data is rarely used in literature because it is not centrally aggregated. Instead, it is published by the individual institutions on their websites. While this did create a significant hurdle due to time effort, CDS data is the only source I identified containing the key variables for this study: The number of international students receiving aid, the amount of average and total aid, and ISE_{ft}.

[7] I only encountered only two institutions that enrolled less than 10 full-time international students per year.

[8] Data pertaining to population restrictions can be found in Appendix C.

[9] The data pulled from Integrated Postsecondary Education Data System (IPEDS) are cost of attendance, total undergraduate enrollment, and acceptance rate. Moreover, I gathered data on sector (e.g., private or public institution), research activity (e.g., low, medium, high according to Carnegie classification), and location (rural/town, suburban, city). More detailed information can be found in Model Specification and Random Effects sections.

[10] More detailed information on the CDS can be found at https://commondataset.org/. In the CDS, international students are referred to as nonresident aliens.

Sample

All data from the CDS had to be aggregated by hand as it is published separately on institutional websites. Since I am gathering CDS data for four variables over eight years, aggregating data for even a single university constitutes a significant time effort.[11] Attempting to include data from all 386 universities exceeded my capacity. Therefore, I decided to consider a smaller sample from this population of 386 universities and chose a random sample of 65 institutions.[12] For each of those 65 universities, data are collected from the 2012/2013 to the 2019/2020 academic year.[13]

CDS data are voluntarily published by the individual universities and colleges. Therefore, the institutions may publish as little or as much data as they want in any given year. I find that there is variation in the completeness of the published data sets over time.[14] While only 38 institutions provided all variables in 2012-2013, 64 provided all data for total aid in 2019-2020.[15] Data from earlier years is more sparse than data from recent years, but the gaps in reporting do not follow a pattern across observed institutional characteristics.

Causal Inference and Interpretation

Due to the rising popularity of causal inference designs, it is worth considering the validity of this study in a causal framework. There currently exists a small amount of relevant causal literature. In general, it can be divided into two categories depending on the type of response variable that is analyzed. First, work like Cornwell et al. (2006) examines the effect of binary treatment on a continuous response variable. Specifically, Cornwell et al. analyze the effect of Georgia's HOPE scholarship program on the state's college student enrollment. Employing a difference-in-differences (DiD) design, Cornwell et al. contrast the state of Georgia with surrounding states. Second, Van Der Klaauw (2002) analyzes the effect of continuous treatment on a binary outcome. Van Der Klaauw exploits a natural experiment to highlight the effect of aid on a student's enrollment decision.

My study differs from these two set-ups in three notable ways. First, I lack a formal control group. Second, the treatment and outcome variables are both continuous (financial aid and ISE_{ft}, respectively). Third, the treatment dosage is awarded over time in varying levels of intensity. This complicates estimation in a canonical DiD[16] design and necessitates a modified inference design.

Callaway et al. (2021) address this problem, offering a potential solution to DiD designs with continuous multi-period (cont.-mp) treatment. Specifically, Callaway et al. show that a two-way fixed effects (TWFE) estimator can be interpreted as the average causal response (ACR) over all doses d under the following five assumptions.

First, Callaway et al. carry over the three basic assumptions that define the binary DiD case. The first assumption is the random sample assumption – meaning that the observed data are independent and identically distributed (iid). Second, the support assumption implies that there is a

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[11]In total, data collection took approximately 8 months.

[12]There is nothing peculiar about choosing exactly 65 institutions, it is merely the maximum number of institutions I could aggregate data from within my time constraints.

[13]All data reported refers the fall semester of the respective academic year, e.g., data from the 2012/2013 academic year refers to fall 2012 data.

[14]In an ideal case, the institution publishes the number of aid recipients (i), the amount of average and total aid (ii), and ISE_{ft} (iii) for any given year.

[15]See Appendix B.

[16]A canonical DiD design refers to the use of a binary treatment variable. That is, there is only one treatment that is applied once. Continuous treatment is a more complicated extension of this situation.

control group of units that are general enough to allow for continuous treatment. The third assumption – the (i) no anticipation/(ii) staggered adoption assumption – refers to (i) units not anticipating treatment and (ii) remaining treated with dose *d* in all subsequent periods upon becoming treated with dose *d* at time *t*.

Additionally, Callaway et al. (2021) argue that extending a canonical DiD design to the cont.-mp scenario requires adding two much stronger assumptions. In binary DiD designs, a parallel trend refers to the parallel behavior of pre-treatment control units and post-treatment treated units. Ergo, in the absence of treatment, the difference between the treatment and control group must remain constant. In continuous DiD designs, this assumption must be extended to a *strong parallel trends* to account for variations of dosage intensity and timing. The strong parallel trends assumption implies that not only the pre- and post-treatment units exhibit parallel behavior, but also the *early* and *late* treated units within the treatment group. When imposed in a cont.-mp situation like this, strong parallel trends restrict the path for both (i) untreated potential outcomes and most importantly (ii) treated potential outcomes. This is crucial since assuming the latter would enable me to justify the interpretation of average causal responses across different dosages and time. If *strong parallel trends* were violated, it would imply an unobserved structural difference between pre-treatment and post-treatment units that would confound estimation.

Lastly, Callaway et al. (2021) formulate an assumption to address treatment effect heterogeneity (TEH). TEH refers to structural differences in the causal response of units to the same dosage. There exists (i) TEH across groups (e.g., the same dosage *d* causing different causal responses across *i* groups at time *t*) and (ii) TEH across dose (e.g., the causal response to increases in the dosage differ within the time period *t*). Moreover, if treatment effect dynamics exist, the causal response to the treatment could vary across time within a timing-group.[17] In summary, Callaway et al.'s fifth assumption assumes that both treatment effect dynamics and TEH do not exist. Notably, the latter two assumptions are significantly stronger than the first three. The strong parallel trends assumption – here the fourth assumption - restricts paths of both untreated and treated potential outcomes such that that all dose groups treated at time t would have had the same path of potential outcomes at every dose. The no treatment effect dynamic/no treatment effect heterogeneity (TEH) assumption – the fifth assumption – assumes homogeneous behavior of treated units across groups, treatment time, and treatment timing group.

In the context of this paper, justifying assumptions 1 - 3 is straightforward. The random sampling strategy and subsequent logarithmic conversions of all financial and enrollment variables yields data that is iid. While the strictly binary DiD case does necessitate a formal control group (Assumption 2), Callaway et al. (2021) find that this requirement relaxes in the cont.-mp case. Estimation with treated units whose treatment differs in dosage and timing voids the need for a formal control group.[18] Assumption 3 is met by the setup of this study. The anticipation problem vanishes since all units in the data are already treated. On the latter note, the staggered adoption situation varies slightly from Callaway et al.'s setup. It is assumed that units stay treated until they leave the institution by any means, e.g., graduation or dropping out. It is also assumed that the financial package does not change during the duration of study.

The strong parallel trends assumption, Assumption 4, would be reasonable in this case. Since one cannot conduct statistical tests for this assumption, I provide a brief logical case. In my empirical specification, I consider the log-transformed versions of total aid and ISE_{ft}. Rather than causally inferring the effect of aid money on enrollment numbers, I would attempt to infer the effect

[17] Timing group refers to the time that arbitrary units *i*, *j*, and *k* received treatment. It does not imply when units *i*, *j*, and *k* received treatment, only whether these units received treatment at the same time.

[18] Callaway et al. (2021): see Appendix C, Assumption 5-MP-Extended.

of total aid changes on enrollment changes. This means that the differing levels of dosages are percentage changes in aid which would likely not change the slopes of the dose-response relationship.

Finding justification for assumption 5 is where the problem lies. In my data, I consider how changes in total aid predict changes in aggregate ISE_{ft} at time t at institution i. In order to rule out TEH, I would have to assume that individual characteristics, such as family income or ability (Dynarski, 2000; Cornwell et al., 2006) are quasi-random across institutions *i* and time periods *t*. This means assuming homogeneity of the causal response across incoming student classes across all institutions and all time periods. I believe this assumption is too strong considering the observational nature of the data used in this study. While the case for Assumptions 1-4 can be made, there is no evidence to justify Assumption 5. It is noteworthy to mention that this study can be extended to a causal study in the future, conditional on addressing the lack of individual student data.

Albeit not qualifying as a causal study, the value of this study lies in the clear connection it makes between changes in financial aid and changes in ISE_{ft}. It is especially useful for institutional decision-makers who seek to better understand the intricacy of the relationship between aid and ISE_{ft}. Future research should address how individual student characteristics influence this relationship. I will briefly address how a causal interpretation relates to the TWFE estimator in the section that details the fixed effects model.

Empirical Strategy and Results

I evaluate how changes in financial aid predict changes in ISE_{ft}. In addition to financial aid, I consider a second variable of interest: Aid concentration. Aid concentration describes how concentrated/spread out aid is within an incoming class of international students. Moreover, I analyze how fixed institutional characteristics influence the effectiveness of aid awards. I focus on some of the most important, per Bicak and Taylor (2020), time-invariant predictors of ISE_{ft} such as research intensity, location, and sector.

Variables of Interest

The primary goal of this paper is to delineate how both financial aid and aid concentration predict ISE_{ft}. Aid concentration is a measure obtained by dividing the total number of international students that receive aid (here *x*) by the total number of international students (here *n*) such that

$$Aid\ Concentration = \frac{\sum_{i=1}^{x} Aid\ Recipients}{\sum_{i=1}^{n} Total\ \mathrm{ISE}ft}$$

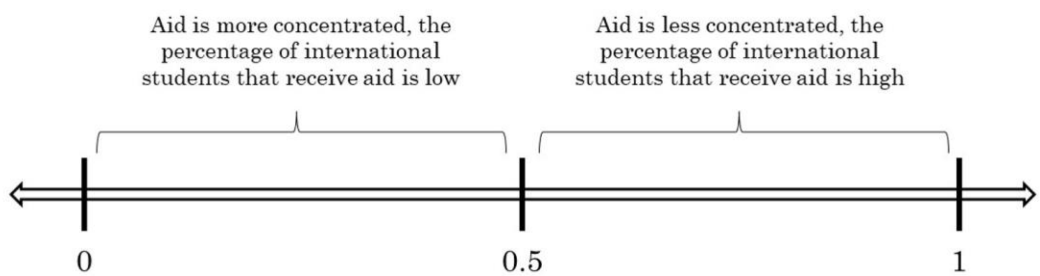
where $x \leq n$; Aid Recipients $\subseteq$ Total ISE_{ft}; and Aid Concentration $\in [0,1]$.

The aid concentration variable not only provides important information, it is also a necessary control. In the CDS data, it was impossible to separate total aid from the aid awarded exclusively to first-time international students. Therefore, part of the fluctuation in total aid may be the result of factors that are not accounted for in the model. For one, total aid may change because international students transfer into the institution throughout the year. Second, fluctuations in total aid may be a result of ISE_{ft} churn (e.g., graduation, transfer-outs, or drop-outs). Third, a student's initial financial aid package may be subject to change over the course of their studies (e.g., due to changes in GPA, aid availability, etc.). While these fluctuations are not captured in the dependent variable (ISE_{ft}), they do affect the total aid values in subsequent time periods. This creates an estimation problem, seeing that changes in total aid are not always subject to the same predictors as ISE_{ft}.

To mitigate this issue, the aid concentration variable accounts for total aid recipients and total ISE_{ft}. By including a measure for not only total ISE_{ft} but also for the number of aid recipients, I can mitigate the effect of ISE_{ft} churn on the estimation precision. Aid concentration – all else equal – captures the presence of transfer students in subsequent periods. Moreover, preliminary analysis shows that changes in average aid are minor in the data, voiding the need to account for total aid variations. Lastly, when interpreted, the aid concentration variable provides information on whether many students receive small amounts of aid or few students receive large amounts of aid. Figure 1 offers a visual explanation.

Figure 1

A visualization of the aid concentration variable



Model Specification

In addition to the two variables of interest – total aid and aid concentration – I include three controls. First, I control for the log of total cost. Total cost is the sum of international tuition expenses, fees, room, board, and books. This is important because aid is only meaningful when relative to cost (Bodycott, 2009; Darby, 2015). Second, I control for the perceived quality of the institution. I do so by using the undergraduate acceptance rate as a proxy for perceived quality of the institution (Bodycott, 2009; Darby, 2015; Mazzarol & Soutar, 2002). A lower acceptance rate correlates with higher rankings, making this a useful continuous approximation of institutional quality. Third, the size of the institution is an important factor (Cantwell, 2019). I control for the log of total undergraduate enrollment. I also use this variable as an alternative to weighting the model. It addresses a potential size effect that may be picked up when not weighting for total undergraduate enrollment. Interestingly, preliminary analysis showed that weighting the model for total enrollment is inconclusive. This is likely because not all control variables require weighting, e.g., acceptance rate.

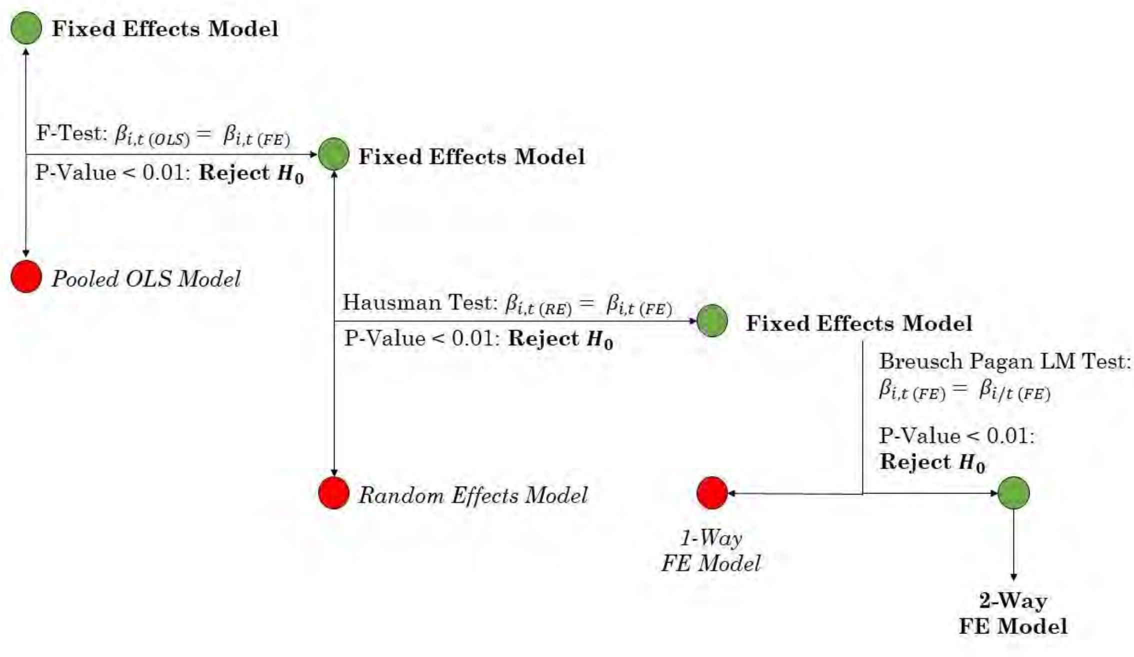
Finally, Bicak and Taylor (2020) mention controlling for the student-faculty ratio to "better control for institutional size and institutional resources" (p. 224-225). Bicak and Taylor suggest that larger institutions, by enrollment or endowment, may be able to staff more faculty members. Bicak and Taylor's reasoning builds on Cantwell (2019) who takes a similar approach by controlling for the logged value of employed faculty. Interestingly, however, the coefficients on student-faculty ratio are a poor predictor of ISE_{ft} across all the institution types that Bicak and Taylor consider. Therefore, I decide against controlling for student-faculty due to a lack of compelling evidence. Leaning on Bicak and Taylor's conclusion, I rely on total undergraduate enrollment to proxy for institutional size and resources.

The Fixed Effects Specification

TWFE specifications have become popular among researchers analyzing panel data. That is because a TWFE model, in contrast to other specifications, considers time and institutional fixed effects. My initial hypothesis was that a TWFE approach is necessary to account for dependencies across units and time. Time periods are expected to be dependent on each other; enrollment in one period is expected to influence the following one(-s). Moreover, a random effects (RE) approach - while accounting for the temporal dimension - would fail to control for institutional fixed effects. A random effects framework would attribute these effects to randomness. An ordinary least squares (OLS) estimator would pool all data, ignoring time- and unit-specific relationships altogether. Economic logic points to a TWFE specification, a choice that is supported by statistical testing summarized in Figure 2.

Figure 2

Model selection and testing



The TWFE model yields a regression specification such that

$$Y_{i,t} = \alpha + \hat{\beta}_{i,t}X_{i,t} + \hat{\delta}_t T_t + \hat{\gamma}_i F_i + \varepsilon_{i,t}, \qquad (1)$$

where $Y_{i,t}$ is the logged first-time international student enrollment of institution i in year t. $X_{i,t}$ is a vector in lieu of the independent variables – the log of total aid, aid concentration, the log of total cost, acceptance rate, and the log of undergraduate enrollment. $\hat{\gamma}$ is the vector of estimated coefficients on the institutional-level fixed effects that control for unobserved characteristics across institutions. The time fixed effect, T_t, controls for the overall enrollment trend in my sample region. The constant a is the intercept in the regression model. $\epsilon_{i,t}$ is the idiosyncratic error term.

Finally, I test this model for heteroskedasticity using a Breusch-Pagan test. I conclude that heteroskedasticity is present and proceed with robust standard errors for my results. Details on hypothesis testing can be found in Appendix D.

It is important to note that the TWFE specification, despite accounting for time and institutional fixed effects, does not represent a reliable, causal estimation strategy by itself. Imai and Kim (2021) show that in general "the standard two-way fixed effects regression estimator does not represent a design-based, non-parametric causal estimator" (p. 413). Imai and Kim assert that "the ability of the [2-way] FE model to simultaneously adjust for [unit- and time-specific confounders]" (p. 405) critically relies upon a robust causal inference design.

This relates closely to Callaway et al. (2021)'s findings. The TWFE parameter can be interpreted as the ACR if and only if Assumptions 1 - 5 hold. Callaway et al. (2021) and De Chaisemartin and d'Haultfoeuille (2020) show that failing to introduce these assumptions introduces selection bias into the TWFE parameter, making a precise causal interpretation impossible. De Chaisemartin and d'Haultfoeuille also show that this leads to a particularly challenging estimation problem when it comes to the TEH issue.

It is worth mentioning that a causal TWFE parameter, assuming Assumptions 1 - 5, can be decomposed into different weighted sums of different treatment effect parameters (Callaway et al., 2021; De Chaisemartin and d'Haultfoeuille, 2020). For instance, reverse-engineering the ACR yields a weighted average of causal response parameters. This is critical insight as it may facilitate the set-up and interpretation of future causal frameworks examining the effect of financial aid on ISE_{ft}. Many researchers do not consider causal parameters other than the average causal effect as a desirable finding. Therefore, understanding the intricacy of the dose-response function in international student aid research is of tremendous value.

Model (3) in Table 1 summarizes the preferred model.[19] Preliminary analysis showed that log(Total Aid) is only significant in conjunction with aid concentration. While an increase in log(Total Aid) increases log(ISE_{ft}), a decrease in aid concentration will set off the effect of that aid. Initial results strengthen this hypothesis. Rather than the amount of aid solely governing the enrollment outcome, predicting ISE_{ft} financial aid depends on both the amount and concentration of aid. The results show that aid allocation towards international students is only effective when the amount is substantial.

The results show that a 10% increase in total aid, will lead to a 1.8% increase in ISE_{ft}, all else equal. Similarly, a 10% increase in aid concentration – spreading aid out by 10% additional percent all else equal – leads to an 8.5% decrease in enrollment. Concentrating large chunks of aid on fewer students is crucial when awarding aid. All else equal, an increase in total aid only results in an ISE_{ft} increase if aid is substantial and concentrated.

The large and significant coefficient on aid concentration is - amongst other things - indicative of the cost barriers that international students face. Many universities charge additional fees to international students, such as the University of Wisconsin Platteville's $1,000 international student fee (Redden, 2015). Moreover, U.S. universities consistently rank amongst the most expensive institutions for international students globally (McCarthy, 2015). For instance, the mean total cost of attendance for one year in my sample of 65 institutions is $48,114[20]. Ergo, universities

[19]Other tables are reported in Appendix E, Table E.1.

[20]This value is the mean value over all 8 years, adjusted to 2020 dollars.

that award only marginal aid amounts to international students will not meet their financial need threshold. While log(Total Aid) is an important and significant predictor of ISE_{ft}, aid awards must be meaningful to be predict enrollment. The results from Table 1 indicate that log(Total Aid) and aid concentration are the most significant time-variant predictors of ISE_{ft}.

Table 1

Results from the fixed-effects model

	Dependent Variable: Log(ISE_{ft})		
	(1)	(2)	(3)
Log(Total Aid)	0.18*** (0.047)	0.18*** (0.048)	0.18*** (0.047)
Aid Concentration	-0.91*** (0.229)	-0.91*** (0.232)	-0.85*** (0.229)
Log(Total Cost)	-0.58 (0.428)	-0.52 (0.410)	-0.85* (0.428)
Acceptance Rate		0.55 (0.422)	0.47 (0.415)
Log(Undergraduate Enrollment)			1.01* (0.405)
Observations	417	415	415
R^2	0.07	0.07	0.09
F Statistic	8.33*** (df = 3; 342)	6.63*** (df = 4; 339)	6.50*** (df = 5; 338)

Note. Robust standard errors in parentheses.
*p<0.1; **p<0.05; ***p<0.01

The Random Effects Specification

In their analysis, Bicak and Taylor (2020) highlight how location impacts international student enrollment. Bicak and Taylor find that urban and suburban institutions have an advantage over universities located in towns and rural areas. Bicak and Taylor also explore how research intensity is related to ISE_{ft}. Using the 2015 Carnegie classifications, Bicak and Taylor find that high-research institutions have an advantage over non-research-intensive ones. Moreover, public universities – on average – have higher ISE_{ft} than private ones. With this insight, I hypothesize that the effectiveness of aid is further impacted by the institution's profile. A dollar of financial aid at an urban institution may not be as effective as a dollar disbursed at a rural one.

This section addresses the principal concern plaguing the design of financial aid: The heterogeneity of treatment effects. This paper falls short of a causal interpretation due to the presence of TEH. Therefore, I build on Bicak and Taylor (2020)'s findings to analyze the relationship between time-invariant institutional characteristics, financial aid, and ISE_{ft}. I do this by regressing ISE_{ft} on interaction terms between the most important (see Bicak & Taylor, 2020) time invariant institutional characteristics and financial aid. A fixed effects model, however, cannot estimate time-invariant variables due to the demeaning process within FE models. Fortunately, a random effects (RE) model can estimate time-invariant variables when the fixed effects are manually specified through interaction terms. Specifying three categories of time-invariant characteristics (see Table 2), I specify a RE model that yields unbiased (Bell & Jones, 2015) results. This specification is an analysis of multilevel institutional characteristics (Bell et al., 2019) and provides granular insight for institutional decision-makers at all types of U.S. universities.

Table 2

Categories of time-invariant characteristics

Location	Research Intensity	Sector
Town/Rural	Low (“Bachelor”)	Private
Suburban	Medium (“Masters”)	Public
City	High (“Doctoral”)	

Through interaction terms with the financial aid variable, I obtain the average marginal effect of either location, research intensity, or sector on aid effectiveness. The specifications for location and research intensity correspond to NCES classifications of degree of urbanization and Carnegie Classification 2015 respectively. Public and private dummy variables are assigned by whether the institution is public or private. It is important to reemphasize that the goal is merely to analyze the coefficients on the interaction terms. The coefficients on all other independent variables in the RE model yield less reliable coefficients than the FE specification due to comparatively inferior sample size (Bell & Jones, 2015; Bell et al., 2019). The RE model yields the following specification:

$$Y_{i,t} = \alpha + \hat{v}_{i,t} D_i \times \log(Aid)_{i,t} + \hat{\beta}_{i,t} X_{i,t} + \hat{\mu}_i D_i + \hat{\delta}_t T_t + \hat{\gamma}_i R_i + \varepsilon_{i,t}, \quad (2)$$

where $Y_{i,t}$ is logged ISE_{ft} of institution i in year t. $\hat{v}_{i,t}$ is the coefficient on the interaction variables where the binary variables D_i interact with $\log(Aid)_{i,t}$ at time *t* and institution *i*. $\hat{\beta}_{i,t}$ are the coefficients of the all independent variables (namely the log of total aid, aid concentration, the log of cost, acceptance rate, and the log of undergraduate enrollment) found in regression (1). $\hat{\mu}_i$ are the coefficients on the respective binary variables (namely location, research, sector). T_t and R_i are the time- and institution-specific random effects estimators, respectively. The constant α is the intercept in the regression model. $\varepsilon_{i,t}$ is the idiosyncratic error term. Breusch-Pagan tests reveal that heteroskedasticity exists for all three regression models necessitating the use of robust standard errors.

The results show how the relationship between financial aid and ISE_{ft} varies within different institutional settings. While the coefficients on the dummy variables support the findings of Bicak and Taylor (2020), I do not interpret them in further detail. That is because Bicak and Taylor offer a more robust analysis of these time-invariant characteristics, owed to a significantly larger sample. In this analysis, the dummy variables outside of the interaction term serve as control terms.

When looking at location-specific characteristics, the Town/Rural interaction term is highly significant. The RE model suggests that rural universities experience an additional 4.5% enrollment increase when compared to non-rural institutions. Therefore, aid results in an additional enrollment boost at rural universities, all else equal. Although less significant, the city model suggests that institutions located in cities exhibit less comparatively. The negative coefficient can be interpreted such that a 10% increase in total aid will result in less powerful enrollment increase (-1.7%), when compared to institutions that are not located in a city. It is important to stress that the negative coefficient does not necessarily refer to an enrollment decrease, rather a less powerful increase/decrease. All in all, it shows that as degree of urbanization decreases, additional international student enrollment can be expected from awarding the same amount of aid. Results for the location model are reported in Table 3 to emphasize their importance. For all other results, see Appendix E, specifically tables E.2 and E.3.

Similarly, as research intensity decreases, the expected enrollment effect from a fixed amount of aid is expected to increase. Note that the dummy variables, in accordance with Bicak and Taylor (2020)'s findings, suggest a higher baseline enrollment. The interaction variables, however, highlight that the potency of aid is even more powerful at institutions that do not have a consistently strong influx of international students. While urban, high research activity institutions ("doctoral") are expected to have higher international student enrollment, their aid can be categorized as less powerful in terms of enrollment outcomes when compared to a rural, less research-intensive school.

The RE model with sector-specific interaction terms suggests that public schools have a higher baseline of international students to begin with (supporting Bicak and Taylor's findings). It is private schools, however, that can boost their ISE_{ft} more efficiently by awarding aid.

The results speak to the profile of a traditionally attractive institution. Higher baseline ISE_{ft} at urban, public, and high research activity universities hints at the structural enrollment advantage these institutions have compared to their counterparts. Interestingly, I find that universities that do not have high baseline ISE_{ft} (e.g., rural) experience additional enrollment boosts when they award aid, all else equal. This is critical insight: Aid can compensate for a lack of the most desirable institutional characteristics; namely an urban location, high research intensity, and public. This finding suggests an opportunity for institutions with less favorable characteristics to harness the power of financial aid to its fullest potential. Figure 3 summarizes the key findings.

Limitations

Cornwell et al. (2006) used a DiD approach to estimate the effect of regional financial aid awards. These authors analyzed how the HOPE scholarship impacts students from different backgrounds. Similarly, Dynarski (2000) examined how financial aid awards affect college attendance. Interestingly, she found that the HOPE Scholarship has widened the gap in college attendance between those from low- and high-income families. Moreover, Stuen and Ramirez (2019) found that country of origin and especially the social networks formed by international students from a specific country exert a significant effect on the inflow of international students. Unfortunately, data availability prevents me from considering individual student data, particularly country of origin, social networks, and income, as predictors of ISE_{ft}. Addressing this principal limitation should be a priority for future research examining the relationship between financial aid and ISE_{ft}.

Most importantly, this study is limited by time constraints. The CDS data has been aggregated by hand from the individual institutions' websites. This was a time-consuming endeavor. Moreover, only some institutions publish the CDS. Even if the CDS was published by a certain institution, it normally was not published for all eight years. The data also rarely distinguishes between need-, merit-, and place-based based aid awards - a contrast to previous studies analyzing the relationship between types of financial aid and domestic students. Although this study is limited by data availability and time constraints, it is the first study measuring how financial aid predicts ISE_{ft}. The author hopes that these findings serve as an incentive for further research in the field of international student enrollment policy.

Table 3

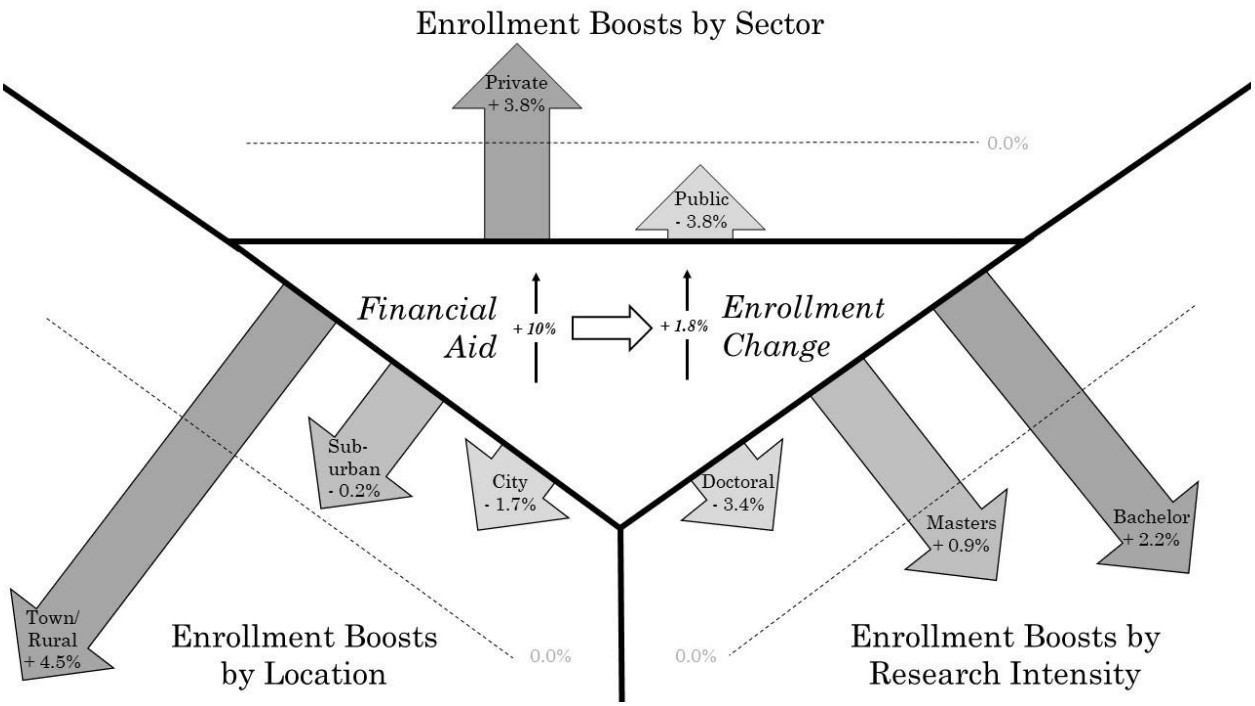
Location-specific interaction terms

	Dependent Variable: Log(ISE_{ft})		
	City Interaction	Suburban Interaction	Town/Rural Interaction
City	2.58* (1.115)		
Suburban		0.11 (1.086)	
Town/Rural			-6.34*** (1.418)
Log(Total Aid)	0.36*** (0.068)	0.26*** (0.051)	0.21*** (0.047)
City × Log(Total Aid)	-0.17* (0.078)		
Suburban × Log(Total Aid)		-0.02 (0.076)	
Town/Rural × Log(Total Aid)			0.45*** (0.096)
Aid Concentration	-1.21*** (0.229)	-1.18*** (0.228)	-1.14*** (0.230)
Log(Total Cost)	1.06*** (0.294)	1.01*** (1.006)	0.87** (0.281)
Acceptance Rate	0.11 (0.374)	0.05 (0.377)	-0.03 (0.372)
Log(Undergraduate Enrollment)	0.61*** (0.103)	0.61*** (0.106)	0.68*** (0.108)
Constant	-17.59*** (3.616)	-15.52*** (3.501)	-13.96*** (3.350)
Observations	415	415	415
R^2	0.29	0.27	0.30
F Statistic	168.21***	152.30***	172.38***

Note. Robust standard errors in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Figure 3

Enrollment boosts by different institutional characteristics



Discussion and Significance

As the first study using CDS data to predict ISE_{ft}, I find that both total aid and aid concentration are significant predictors of ISE_{ft}. When contrasting financial aid to other predictors, aid and its concentration are the only significant time-variant predictors. Interestingly, aid and its concentration differ substantially by institutional characteristics. When introducing time-invariant dimensions like location, research intensity, and sector, random effects regressions reveal substantial differences in the effectiveness of institutional aid. Traditionally less attractive institutions, e.g., rural, private, and low research activity universities, exhibit substantial marginal enrollment boosts when awarding aid.

At their core, these findings underscore how effective aid is as an incentive for ISE_{ft}. However, it is important to note that aid is not only effective. Financial aid is also more beneficial than other enrollment management tools. One, aid is crucial for the well-being of international students. A study on Chinese college students finds that students with more aid are more successful academically than those without (Yang, 2011). Yang argues that this stems from financial aid inducing more studying effort. Moreover, Boatman and Long (2016) show that aid recipients were more likely to engage with peers on schoolwork outside of class. While the study is performed on domestic minority students, the insight is transferable to international students. Boatman and Long conclude that aid recipients were much more likely to participate in community service activities and marginally more likely to participate in other extracurricular activities than the control group. Finally, aid has the potential of increasing equity in the educational process. For instance, need-based aid can subsidize education for low-income international students.

On the contrary, literature like Minaya et al. (2022) demonstrates that aid, e.g., merit-based aid, can in fact exacerbate inequality in higher education. While a detailed discussion on the mechanics of aid awards lies beyond the scope of the paper, it is critical to note that aid must be awarded carefully. Aid – if used with the desire the enhance equity – has the potential to make post-secondary education in the U.S. more affordable and accessible to international students.

Aid is important because it is beneficial to the recipients. Interestingly, is also beneficial for institutions via the presence of international students. With international students counting amongst the most competitive scholars at universities, their enrollment boosts the rankings and renown of institutions (McCormack, 2007). Chellaraj et al. (2008) estimate that a 10% increase in foreign graduate student enrollment leads to a 4.5% increase in patent applications. International students, therefore, may contribute to increased research funding and perceived attractiveness of the university. This leads to better competitive rankings and therefore is an important contributor to domestic student enrollment.

Moreover, international students bring financial stability to institutions by offsetting domestic enrollment fluctuations. This becomes increasingly important as a U.S.-wide enrollment decline may result from changing demographics (Heckman & LaFontaine, 2010). Additionally, international students define the personality of a university (Hegarty, 2014) and significantly contribute to student body diversity.

The value of international students can also be quantified on the national level. As an important source of revenue, they contribute to local economies through tuition payments, living, and transportation expenses. The Association of International Educators (NAFSA) (2020) estimates that for the combined spending activity of eight international students, three U.S. jobs are created and supported. In addition to direct economic impact, international students also benefit the U.S. economy through entrepreneurial activity. International students bring skills and creativity that contribute to innovation and economic growth (Tremblay, 2005). According to Institute of International Education (IIE) (2021) calculations, these contributions resulted in over $27 billion added economic value to the U.S. economy in 2013/2014 alone. In summary, aid is not only an important enrollment management tool but also a way to financially support universities and economies.

Implications for Policy and Practice

This paper's findings can motivate enrollment managers to make education more accessible. Mause (2009) highlights that while U.S. higher education has become more market-driven, the industry's mandate to serve local communities with affordable and high-quality education has been neglected. In conjunction with rising tuition rates, stagnant – even declining – rates of financial aid and funding has contributed to growth in income inequality (Alon, 2009). In a globalizing higher education market, this trend is becoming noticeable on the global level, too. Being caught in a "reputation race" (Van Vught, 2008, p. 168), literature has labeled HEI spending on marketing and promotion as "excessive and socially wasteful." (Mause, 2009, p. 1108). Financial aid, therefore, is an enrollment tool that not only meets the enrollment goal of institutional decision-makers, but it also makes education more attainable. Combining the findings of this paper with existing literature on higher education equity and access, financial aid is a 'win-win' policy tool. It unifies the market-driven perspective of university administrators with the equity mandate of HEIs.

Second, this work can reshape competition amongst institutions in the higher education sector. Per Bicak and Taylor (2020), a university's time-invariant characteristics play the largest part in its perceived attractiveness. This makes competing for enrollment challenging for universities with a less attractive profile, resulting in a structural disadvantage. Financial aid counteracts this competitive disadvantage through the enrollment boosts less attractive institutions exhibit when awarding aid to international students. In the long term, these marginal enrollment boosts can enable institutions to pursue an internationalization strategy (Bagley and Portnoi, 2014; Knight, 2004). Seeing that international students are closely related to innovation and rankings, institutions that are less competitive for domestic students may enhance their status and renown by attracting ISE_{ft} through aid awards. While this constitutes a promising strategy for these institutions, adapting a more critical stance is equally necessary. Academic institutions do not exist in a vacuum, but rather within their respective communities. Especially in rural or conservative communities, pursuing a strict internationalization strategy may cause friction between the institution and members of the community. International students may be seen as unwanted or even as crowding out domestic talent. Therefore, it is necessary to note that an internationalization strategy is subject to social and cultural constraints, e.g., the attitude of the community. Stier (2004) offers further critical thought on both the ideology and practice of internationalization in higher education. Despite concerns regarding the implementation of an internalization strategy, strong empirical evidence still supports potential of an internationalization strategy remains strong. Bound et al. (2020) demonstrate that non-resident students do not crowd out resident students.[21] Therefore, institutions must acknowledge the need for proactive communication with the community. Through collaboration, the presence of international students may result in mutual benefit, e.g., boosting local economic spending. Despite valid criticism, awarding more aid to international students still constitutes a promising strategy for rural, small, and low research institutions to compete in a dynamic higher education market.

Lastly, recognizing the potential of international student aid is crucial for policymakers on the local, state, and federal levels. International students yield both local and national economic benefits through spending, investment, innovation, and entrepreneurial activity. As the U.S. is slowly losing its monopolistic grip on international talent (Douglass & Edelstein, 2009) and therefore its control over higher education as a prime export good (Li, 2017), its economy is put at risk. Regulators must recognize that funding international student education is a direct investment in economic growth, output, and competitiveness. It enables them to effectively fight economic challenges associated with changing demographics, structural change in local economies (Owens et al., 2011), and technological competition with countries like China. Per Marginson (2006), a global research university is critical to many nations' missions to remain key players in the global knowledge economy.

While the U.S. government is not currently considering any federal aid programs for foreign students, it exerts significant influence on ISE_{ft} through other means. Most notably, government support can be observed through labor market openness and efforts directed at reducing immigration barriers. Specifically, in line with Shih (2016)'s findings, the H-1B visa program offers a reliable way of measuring U.S. labor market openness towards international students. Initially, it is surprising to see that the cap on H-1B issuances has remained constant[22] since 2006 (American Immigration Council (AIC), 2021), suggesting a lack of correlation with political administrations. However, a closer look at the H-1B scheme reveals that the denials of H-1B petitions do closely correlate with the restrictive immigration policies of the Trump administration. According to the National Foundation for American Policy (National Foundation of American Policy (NFAP)

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[21]Bound et al. do not distinguish between international and out-of-state students in their work. Resident students are in-state students.

[22]Technically, it has remained constant since 2004. However, in 2006, 20,000 additional visas were allotted to graduate degree holders from U.S. universities.

(2022)), the denial rate for H-1B petitions sank to 4% after reaching a record high of 21% in 2019 during the Trump administration. This recent decrease in H-1B denial rates gives hope for the future. An open regulatory attitude could sway more[23] top international talent to stay in the U.S. long-term, counteracting the enrollment decline. With an institutional commitment to support international students financially and government support, foreign students can contribute to sustained economic growth of the United States of America.

[23]Per Chellaraj et al. (2008): Only 15% of international students stay in the U.S. long-term.

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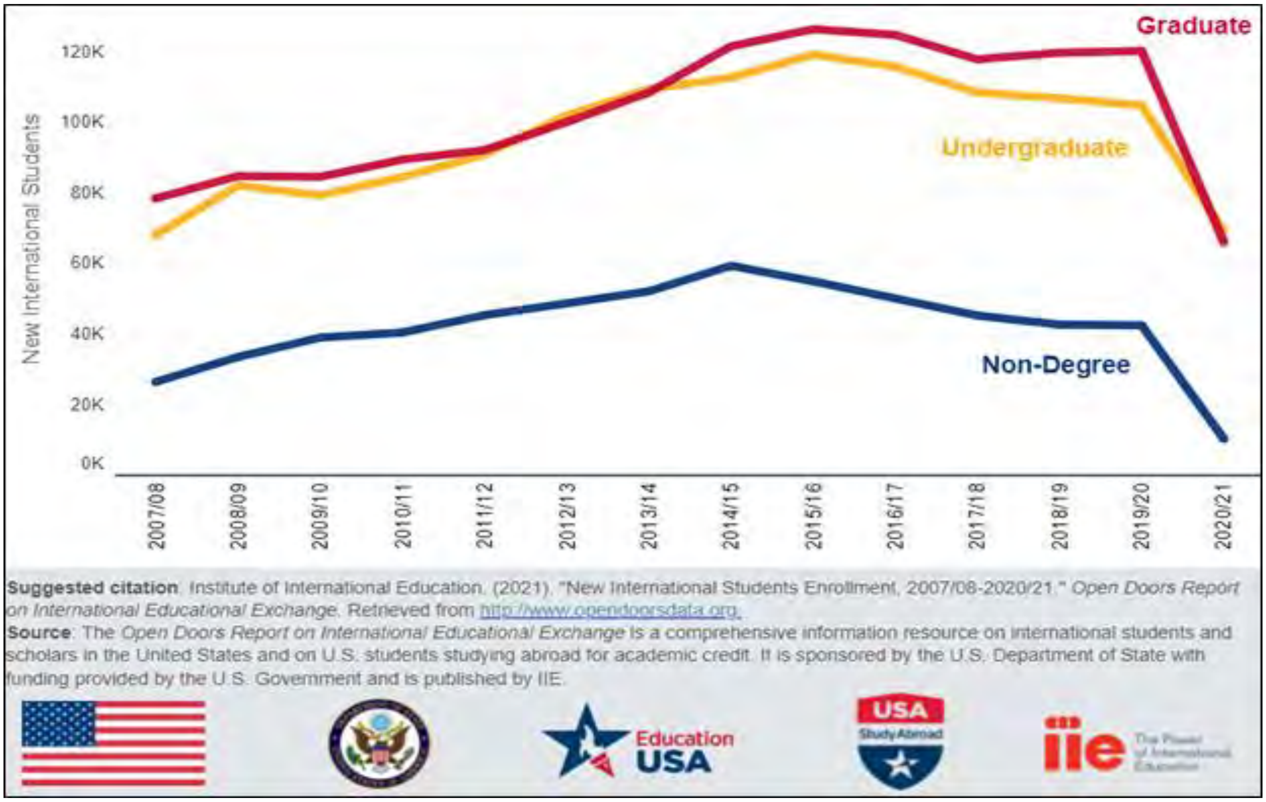
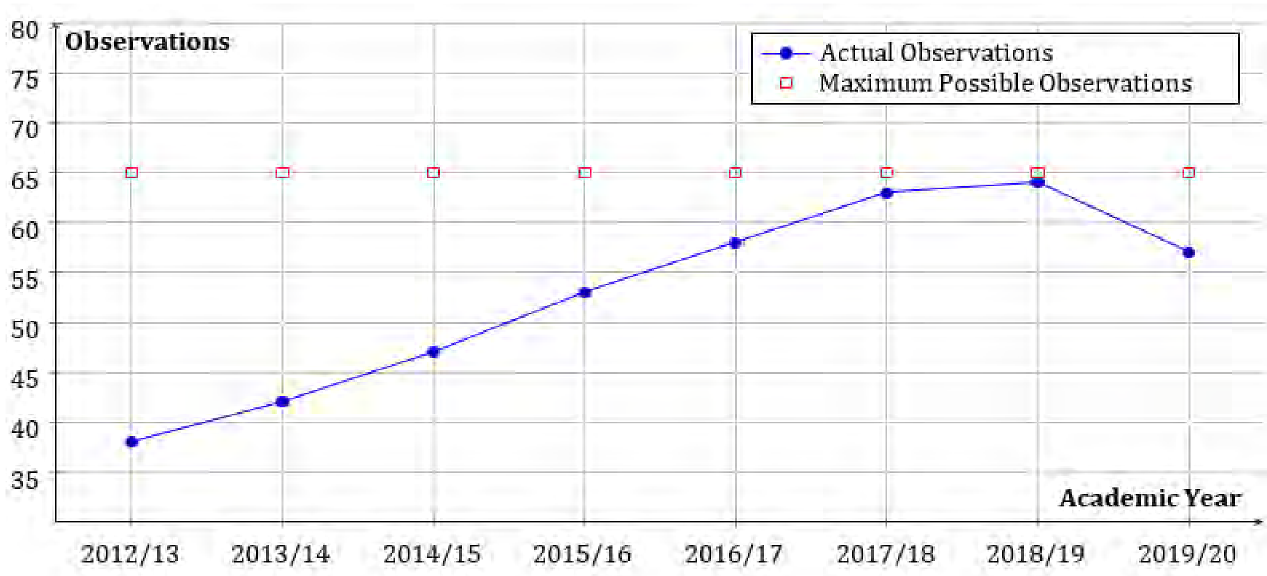
Appendix A

New international student enrollment since 2007/08



Appendix B

Observations of the total aid variable in the CDS, by year



Appendix C

Table C.1

Preliminary restrictions to population

	Number	Percentage of Population	Comments
Total # of Institutions	444	100%	Population before Restrictions
- # of for-profit institutions	- 24	- 5%	
- # of special-interest institutions	- 34	- 8%	
Remaining # of institutions	386	87%	Population after Restrictions

Appendix D

Table D.2

Details on hypothesis testing

Model	Hypothesis	Test	P-Value	Conclusion
Equation(1)	OLS vs. FE	F-Test	< 0.01	Reject H_0
Equation(1)	RE vs. FE	Hausman Test	< 0.01	Reject H_0
Equation(1)	1-way FE vs. 2-way FE	Breusch-Pagan Lagrange Multiplier Test	< 0.01	Reject H_0
Equation(1)	Heteroskedasticity	Breusch-Pagan Test	< 0.01	Reject H_0
Equation (2) (Location: City)	Heteroskedasticity	Breusch-Pagan Test	< 0.01	Reject H_0
Equation(2) (Location: Suburban)	Heteroskedasticity	Breusch-Pagan Test	< 0.01	Reject H_0
Equation(2) (Location: Town/Rural)	Heteroskedasticity	Breusch-Pagan Test	< 0.01	Reject H_0
Equation(2) (Research: Doctoral)	Heteroskedasticity	Breusch-Pagan Test	< 0.01	Reject H_0
Equation(2) (Research: Masters)	Heteroskedasticity	Breusch-Pagan Test	< 0.01	Reject H_0
Equation(2) (Research: Bachelor)	Heteroskedasticity	Breusch-Pagan Test	< 0.01	Reject H_0
Equation(2) (Sector: Private)	Heteroskedasticity	Breusch-Pagan Test	< 0.01	Reject H_0
Equation(2) (Sector: Public)	Heteroskedasticity	Breusch-Pagan Test	< 0.01	Reject H_0

Appendix E

Table E.1

Results from OLS, RE Models compared to the preferred (3) FE Model

	Dependent Variable: Log(First Enrollment)		
	(OLS)	(RE)	(FE)
Log(Total Aid)	0.37*** (0.042)	0.26*** (0.046)	0.18*** (0.047)
Aid Concentration	-1.46*** (0.183)	-1.20*** (0.229)	-0.85*** (0.229)
Log(Total Cost)	2.04*** (0.267)	1.01*** (0.298)	-0.85* (0.428)
Acceptance Rate	-0.46 (0.241)	0.55 (0.375)	0.47 (0.415)
Log(Undergraduate Enrollment)	0.64*** (0.092)	0.606*** (0.106)	1.01* (0.405)
City	0.61*** (0.097)		
Suburban	0.13 (0.121)		
Doctoral	-0.96*** (0.137)		
Masters	-0.98*** (0.117)		
Private	-0.94*** (0.195)		
Constant	-27.066*** (2.717)	-15.446*** (3.502)	
Observations	415	415	415
R^2	0.78	0.27	0.09
F Statistic	143.04*** (df = 10; 404)	150.22***	6.50*** (df = 5; 338)

Note. Robust standard errors in parentheses. In the OLS model, I control for institutional fixed effects by including the dummies specified in Table 2. To avoid multicollinearity, I include n – 1 binary variables relating to location (3 – 1 = 2), research (3 – 1 = 2), and sector (2 – 1 = 1), respectively.
*p<0.1; **p<0.05; ***p<0.01

Table E.2

Research-specific Interaction Terms (RE Model)

	Dependent Variable: Log(ISE_{ft})		
	Doctoral Interaction	Masters Interaction	Bachelor Interaction
Doctoral	5.19*** (1.004)		
Masters		-2.10 (1.389)	
Bachelor			-1.96 (1.113)
Log(Total Aid)	0.40*** (0.064)	0.21*** (0.045)	0.20*** (0.050)
Doctoral × Log(Total Aid)	-0.34*** (0.069)		
Masters × Log(Total Aid)		0.09 (0.102)	
Bachelor × Log(Total Aid)			0.22** (0.075)
Aid Concentration	-1.28*** (0.231)	-1.17*** (0.225)	-1.30*** (0.223)
Log(Total Cost)	0.73* (0.299)	0.67* (0.298)	0.98*** (0.291)
Acceptance Rate	-0.05 (0.365)	-0.002 (0.364)	0.05 (0.358)
Log(Undergraduate Enrollment)	0.45*** (0.134)	0.55*** (0.099)	0.93*** (0.125)
Constant	-13.16*** (3.784)	-10.31** (3.566)	-17.48*** (3.457)
Observations	415	415	415
R^2	0.32	0.32	0.35
F Statistic	196.32***	192.85***	223.90***

Note. Robust standard errors in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table E.3

Sector-specific Interaction Terms (RE Model)

	Dependent Variable: Log(ISE_{ft})
	Private Interaction
Private	-4.86*** (1.162)
Public	
Log(Total Aid)	0.15** (0.051)
Private × Log(Total Aid)	0.38*** (0.078)
Aid Concentration	-1.21*** (0.219)
Log(Total Cost)	0.65 (0.378)
Acceptance Rate	0.33 (0.370)
Log(Undergraduate Enrollment)	0.75*** (0.141)
Constant	-11.87** (3.772)
Observations	415
R^2	0.33
F Statistic	199.72***

Note. Robust standard errors in parentheses.
*p<0.1; **p<0.05; ***p<0.01