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The Effect of Institutional Aid on International Student Enrollment:
A Fixed-Effects Approach

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Daniel is an Analyst at Amend Consulting as well as the President and Founder of Neo Consulting, a student initiative that is dedicated to empowering underrepresented small businesses through consulting services in the field of data analytics. As he demonstrates in his recent TEDx talk, Daniel is passionate about the transformative power of storytelling and helping others tell their stories with data.

Daniel's current research explores the effect of institutional aid on international student enrollment through the use of a two-way fixed-effect model on a sample of universities from the Great Lakes region.

The Effect of Institutional Aid on International Student Enrollment: A Fixed-Effects Approach

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Abstract

Since 2016, international student enrollment declined at U.S. colleges and universities. This trend disrupts a decade-long upwards trajectory of international student enrollment rates. Previous research has demonstrated that various political, social, and macroeconomic factors influence an international student's decision to study abroad in the U.S. Certain institutional characteristics also significantly predict international student enrollment (Bicak and Taylor, 2020). Using data from the Common Data Set and the National Center for Education Statistics, I examine the role that financial aid plays as an enrollment incentive for undergraduate students. Working with a random sample of 4-year, Title-IV participating institutions from the Great Lakes region, I utilize a two-way fixed effects model to answer this question. My findings indicate that financial aid is amongst the most powerful enrollment incentives, when compared to other enrollment tools. Nevertheless, financial aid only seems to matter when large amounts of it are concentrated on a few students. Institutional fixed effects, i.e. the location, research activity, or sector, further influence the effectiveness of aid. Using random effects models, I find that non-urban, less research-intensive, private institutions profit most off awarding financial aid to international students. Results from this work could help institutional leaders revitalize international student enrollment.

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1. Introduction

Since the Fall of 2016[1], international student enrollment (ISE) has been steadily declining at U.S. universities[2]. Sometimes described as the "Trump Effect," Bellmore and Hacker (2020) claim that factors like anti-immigration rhetoric, increases administrative hurdles, and personal safety threats induced the sudden ISE decline. Additionally, an increasingly challenging job market has made studying in the U.S. less attractive to international students. Shih (2016) finds that H-1B visa issuances to a country are positively and significantly related to the number of international students from that country. As tuition costs increase, international students rely on career outlooks to justify the expensive decision to study abroad.

Unfavorable circumstances on the national level prompt the question on how this trend can be reversed, or at least mitigated. While this issue can be approached from various policy angles, I focus exclusively on the institutional level. To incentivize enrollment for certain student groups, institutions have a wide array of tools available to them. Arguably, the most intuitive tool of all is the disbursement of financial aid in the form of scholarships and grants. Universities use aid to control student body size, diversity, or make-up. An example are universities with distinct minority-focused scholarship program, i.e. the *Turner Scholars* program at the University of Cincinnati.

For international students, enrollment incentives function similarly – with one important exception. On average, international students face higher costs than domestic students because of higher administrative, educational, and living expenses. Therefore, I seek to find out how financial aid impacts ISE specifically. I provide answers to two research questions, critical to the current situation in the international education sphere:

> R1: How does total institutional aid and aid concentration affect new ISE in general?
>
> R2: How does location, research intensity, and sector influence the effectiveness of institutional aid?

This case study refines the insight of existing research on ISE incentives. While previous research, i.e. Bicak and Taylor (2020), illustrate the role of aid on the undergraduate level in general; they do not distinguish between aid awarded to

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[1] Institute of International Education, Open Doors Report 2020; Appendix A.
[2] The author uses the terms college, institution, school, and university interchangeably.

domestic vs. international students. The Common Data Set (CDS) serves as a unique opportunity to distinguish between domestic and international student aid.

2. Methodology

2.1 Sampling Strategy and Data

This study focuses exclusively on students at the undergraduate level. My observations are limited to 4-year, Title-IV participating universities. This is due to structural differences of 2-year colleges, and the different motivations associated with attending one (Zhang and Hagedorn, 2018). Moreover, I exclude for-profit institutions and special interest colleges, i.e. bible colleges. While the number of for-profit institutions in the sample region is negligible in the first place, this approach also helps minimize the bias associated with enrollment behavior at special-interest schools. Since I am interested in exploring the effect of institutional aid over time, I only consider universities that award at least some aid to international students in at least two years. Moreover, I exclude a total of two universities that enroll less than ten international students per year. This is because ISE fluctuations can be assumed to be largely random. Therefore, the sampling frame is only minimally altered.

I construct a random sample of universities in the Great Lakes region, spanning the states of Ohio, Indiana, Illinois, Michigan, and Wisconsin. A more strategic approach to sampling helps minimize endogeneity associated with location. For example, states like California possess attractive geographic qualities that influence the perceived attractiveness of an institution. With these five states exhibiting similar geographic characteristics, I do not control for regional differences.

While data is gathered from the National Center for Education Statistics (NCES), the CDS offers the most exclusive information. I extract information on total international student aid, the number of aid recipients, and first-time, full-time ISE[3] from the CDS. I aggregate the CDS data by hand from the respective universities' websites. Not all universities publish their CDS as it is shared on a voluntary basis. My panel data set is unbalanced because colleges frequently publish only a select number of years. Descriptive statistics show that observations increase by year, suggesting that more recent data is published more frequently. While this raised concerns initially, there is no evidence that observations are not missing at random. Descriptive statistics suggest that missing values are relatively even between

[3] In the Common Data Set, the international students are referred to as nonresident aliens. I use these terms interchangeably.

different institutional types.[4] This is important insight that further reduces the risk of biased results.

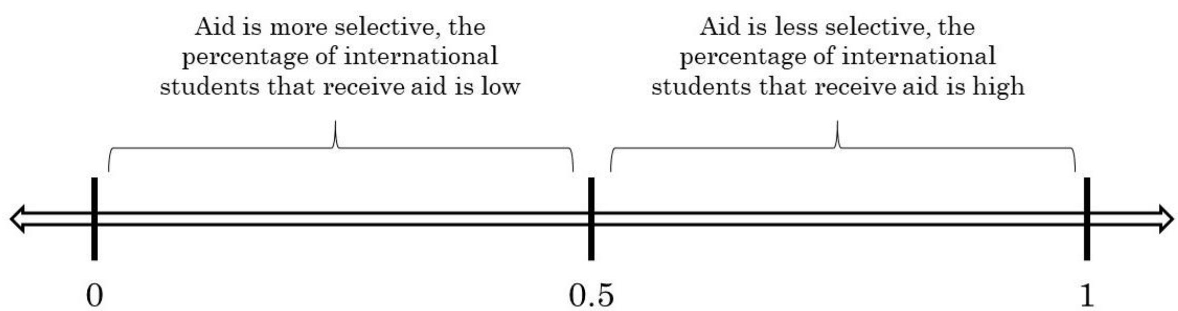
In total, my sample consists of 65 institutions observed from the 2012/2013 to the 2019/2020 academic year. There are a total of 386 institutions in my sample region that meet my sampling criteria. It is important to note that all data reported refers the fall semester of the respective academic year, i.e. data from the 2012/2013 academic year refers to Fall 2012. All financial variables were converted to 2020 dollars using the Commonfund Institute's (2018) Higher Education Price Index (HEPI).

2.2 Variable Selection

The variations in size amongst institutions poses an initial challenge. For small universities, an enrollment increase of 100 students is more significant than for a large university. To address this issue, I apply log transformations to all financial and enrollment variables[5]. This enables me to interpret my results as percentage changes rather than absolute values. Additionally, developing my model in a log-log[6] framework addresses outliers in the data set.

The goal is to delineate the effect of two variables of interest: The effect of (i) Total Aid and (ii) Aid Concentration. While the total aid variable is simply the total aid awarded to all international students in a given year, the aid concentration variable merits further explanation. It is a measure describing whether many students receive little aid – or a few students receive a lot of aid. It is obtained by dividing the total number of international students that receive aid over the total number of full-time international students. The visualization below offers a visual explanation.

Figure 1: A visualization of the Aid Concentration variable.



[4] Appendix B.
[5] I refer to logarithmic transformations as log hereafter. I do not log ratios, i.e. aid concentration.
[6] A log-log model refers to logging both the dependent and at least one independent variable.

My dependent variable is the number of first-time, full-time, degree-seeking international students.[7] In addition to my two variables of interest, (i) Total Aid and (ii) Aid Concentration, I control for other variables in my regression model. Firstly, I control for the log of total cost. Total cost is the sum of international tuition expenses, fees, room, board, and books. It is important to control for cost as aid is only meaningful when it is relative to it.

Further reasoning for the control variables is influenced by the findings of Bicak and Taylor (2020), whose work is fundamental to the construction of this model. They find that perceived quality of the institution is significant. Therefore, I control for the undergraduate acceptance rate as a proxy for perceived quality of the institution. A lower acceptance rate correlates with higher rankings, making this a useful continuous variable in my model.

Lastly, Bicak and Taylor (2020) find that the size of the institution is an important factor. Therefore, I control for the log of total undergraduate enrollment. I also use this variable as an alternative to weighting the model. An initial concern were the size effect that may be picked up when not weighting for total undergraduate enrollment. Preliminary analysis shows, however, that weighting the model for total enrollment is inconclusive as not all variables require weighting.

Bicak and Taylor (2020) mention controlling for the student-faculty ratio to "better control for institutional size and institutional resources." They suggest that larger institutions, by enrollment or endowment, may be able to staff more faculty members. Cantwell (2015) takes a similar approach by controlling for the logged value of employed faculty. Seeing that I am limited by a small data set, I decide against including this measure. However, I do find that the effect of size and resources is partially picked up by the acceptance rate and total undergraduate enrollment.

2.3 Model Selection and Robustness

To evaluate *R1*, the author could choose between fixed-effects (FE), random effects (RE), or pooled ordinary least squares (OLS) models. In order to evaluate whether a pooled OLS or a FE model is the best approach, I perform a F-test under the null hypothesis that $\beta_{i,t\,(OLS)} = \beta_{i,t\,(FE)}$. A p-value of 2.2e-16 (< 0.01) leads me to reject the null, suggesting that the coefficients ($\beta_{i,t\,(OLS)}$ *and* $\beta_{i,t\,(FE)}$) differ from each other. I conclude that the OLS model is inconsistent and choose the FE model over it. This result is consistent with economic logic. It is expected that the time periods are not

[7] First-time, full-time, degree-seeking international students are referred to as first-time international students hereafter.

independent from one another. Therefore, we would need a more refined methodology than a pooled OLS.

Secondly, I choose whether to use a FE or RE approach to answer question *R1*. This question is less intuitive than the last one. To choose between a FE and RE model, I conduct a Hausman test under the null hypothesis that $\beta_{i,t\,(FE)} = \beta_{i,t\,(RE)}$. A p-value of 3.949e-06 (< 0.01) leads me to reject the null, suggesting that the coefficients differ from each other ($\beta_{i,t\,(FE)} \neq \beta_{i,t\,(RE)}$). I conclude that the RE model is inconsistent and choose the FE model.

Now, I need to decide whether to use one-way or two-way FE model. A two-way FE model would consider both institutional (i) and time (t) fixed effects, where a one-way FE model would only consider one or the other. To answer this question, I perform a Breusch-Pagan Lagrange multiplier (LM) test. Under the null hypothesis that $\beta_{i,t\,(FE)} = \beta_{i/t\,(FE)}$, a p-value of 2.2e-16 (< 0.01) leads me to reject the null. I conclude that I will use a two-way FE model to evaluate research question *R1*.[8]

Combining these findings with Section 2.2 yields our final regression model, such that:

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

Where $log(Y_{i,t})$ is the logged dependent variable of institution i in year t. The constant α is the intercept in the regression model. $\hat{\gamma}_i$ is the vector of estimated coefficients on the institutional-level fixed effects that control for unobserved characteristics across institutions. The time fixed effect, F_t, controls for the regional[9] enrollment trend. $X_{i,t}$ is a vector in lieu of the independent variables, specified in Section 2.2. $\varepsilon_{i,t}$ is the idiosyncratic error term.

Lastly, I test this model for heteroskedasticity using a Breusch-Pagan test. With a p-value = 8.576e-06 (< 0.01), I reject the null hypothesis that the errors have constant variance. I conclude that heteroskedasticity is present and proceed with robust[10] standard errors for my results.

[8] Results from OLS, and RE models are shown in Appendix C.
[9] The Great Lakes region, my sample region.
[10] White Standard Errors

2.4 Limitations

This study is limited by the author’s time constraints. The CDS data had to be aggregated by hand from the individual institution’s websites. This has been a time-consuming endeavor. Moreover, data availability is a limiting factor. Only some institutions publish the CDS. Even if the CDS is published by a certain institution, it normally was not published for all eight years.

Although this case study is limited in scope, it is a necessary first step to assess the importance of financial aid for international students. For the first time, financial aid data specific to nonresident aliens is incorporated in a quantitative framework like this. The author hopes that these findings serve as an incentive for further research in the field of international student enrollment policy. In this critical time, institutions must improve scholarly diversity and international scholarship on campuses in the U.S.

3. Results

3.1 General Findings (R1)

Table 1: General Results.

	Dependent Variable:		
	Log(First Enrollment)		
	(1)	(2)	(3)
Log(Total Aid)	0.18 ***	0.18 ***	0.18 ***
	(0.047)	(0.048)	(0.047)
Aid Concentration	-0.91 ***	-0.91 ***	-0.85 ***
	(0.229)	(0.232)	(0.229)
Log(Total Cost)	-0.58	-0.52	-0.85 *
	(0.428)	(0.410)	(0.428)
Acceptance Rate		0.55	0.47
		(0.422)	(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 ***	6.63 ***	6.50 ***
	(df = 3; 342)	(df = 4; 339)	(df = 5; 338)
Note: Robust standard errors in parentheses.		*p<0.1; **p<0.05; ***p<0.01	

In this table, I present my three base models. Preliminary analysis showed that total aid is only significant in conjunction with aid concentration. My initial hypothesis was that total aid and aid concentration function as antagonists. The results strengthen this initial hypothesis, seeing that the respective coefficients have opposite signs.

My preferred model is (3), as illustrated in section 2.2. The results show that a 10% increase in total aid, will lead to a 1.8% increase in first-time international student enrollment, all else equal. Similarly, a 10% increase in aid concentration – ergo spreading aid out by 10% additional percent – leads to an 8.5% decrease in enrollment. It shows that 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 increase if aid is substantial.

These results are indicative of the substantial cost barriers that international students face. Many universities charge additional fees to international students, i.e. 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[11] in my sample is $ 48,114. Ergo, universities that award marginal aid to international students will not meet their financial need threshold. While total aid is an important and significant predictor of ISE, aid awards must be substantial and intentional to be successful.

Lastly, it is important to note that aid and aid concentration seem to be the only[12] significant predictors of international student enrollment. In an unfavorable political environment, institutional leaders can utilize financial aid as an effective and reliable enrollment stimulant.

Per Bicak and Taylor (2020), there are time-variant and time-invariant institutional characteristics that attract international students. The results from Table 1 illustrate that total aid and aid concentration are the most significant time-variant predictors of ISE. Albeit, they find that some of the strongest predictors of ISE are in fact time-invariant factors. In their analysis, Bicak and Taylor explore how location impacts international student enrollment. They find that urban and suburban institutions have an advantage over universities located in towns and rural areas. Moreover, they explore how research activity affects ISE. Using the 2015 Carnegie classifications, they find that high-research institutions have an advantage over non-research-intensive ones. Furthermore, they reveal that public universities – on average – have higher ISE than private ones. With this insight, the author formulates the hypothesis that the effectiveness of aid on ISE is in fact impacted by these time-invariant characteristics.

3.2 The Effect of Time-Invariant Characteristics on Aid Effectiveness (R2)

To answer this question (*R2*), I introduce interaction terms into my regression model. Going from my preferred model, I interact the logged total aid variable with a binary variable describing either location, research intensity, or sector. 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.

[11] This value is the mean value over all 8 years, although adjusted to 2020 dollars.
[12] The only significant time-variant predictors.

Table 2: Specifying the binary variables for the interaction terms.

Location	***Research***	***Sector***
Town/Rural	Bachelor	Private
Suburban	Masters	Public
City	Doctoral	

Because of the time-invariant dummy variables in the interaction terms, I am limited to using a random effects model, assuming no fixed effects by institutional sector. Therefore, the fixed effects framework of regression (1) is no longer applicable. The random effects framework, as well as the binary variables and interaction terms, yield a new model, such that:

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

Where $log(Y_{i,t})$ is the logged dependent variable of institution i in year t. The constant α is the intercept in the regression model. $\hat{\beta}_{i,t}$ are the coefficients of the control variables established in regression (1), and $\hat{\mu}_d$ are the coefficients on the respective binary variables. $\hat{v}_{i,t}$ is the coefficient on the interaction variables, where the binary variables $\widehat{D}_i$ interact with log(Aid)[13] at time t and institution i. $\hat{R}_t$ and $\hat{R}_i$ are the time- / and institution-specific random effects estimators, respectively. $\varepsilon_{i,t}$ is the idiosyncratic error term.

Breusch-Pagan tests reveal that heteroskedasticity exists at α = 0.01. Therefore, I use robust standard errors as I proceed.

[13] In the interest of brevity, Log(Aid) is used as an abbreviation for log(Total Aid) here.

Table 3: Location-specific interaction terms

	Dependent Variable:		
	Log(First Enrollment)		
	(City)	(Suburban)	(Town/Rural)
City	2.58 *		
	(1.115)		
Suburban		0.11	
		(1.086)	
Town/Rural			-6.34 ***
			(1.418)
Log(Total Aid)	0.36 ***	0.26 ***	0.21 ***
	(0.068)	(0.051)	(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 ***	-1.18 ***	-1.14 ***
	(0.229)	(0.228)	(0.230)
Log(Total Cost)	1.06 ***	1.01 ***	0.87 **
	(0.294)	(1.006)	(0.281)
Acceptance Rate	0.11	0.05	-0.03
	(0.374)	(0.377)	(0.372)
Log(Undergraduate Enrollment)	0.61 ***	0.61 ***	0.68 ***
	(0.103)	(0.106)	(0.108)
Constant	-17.59 ***	-15.52 ***	-13.96 ***
	(3.616)	(3.501)	(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

Table 4: Research-specific interaction terms

	Dependent Variable:		
	Log(First Enrollment)		
	(Doctoral)	(Masters)	(Bachelor)
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 5: Institution Sector-specific interaction terms

	Dependent Variable:	
	Log(First Enrollment)	
	(Private)	(Public)
Private	-4.86 ***	
	(1.162)	
Public		4.86 ***
		(1.612)
Log(Total Aid)	0.15 **	0.53 ***
	(0.051)	(0.067)
Private*Log(Total Aid)	0.38 ***	
	(0.078)	
Public*Log(Total Aid)		-0.38 ***
		(0.078)
Aid Concentration	-1.21 ***	-1.21 ***
	(0.219)	(0.219)
Log(Total Cost)	0.65	0.65
	(0.378)	(0.378)
Acceptance Rate	0.33	0.33
	(0.370)	(0.370)
Log(Undergraduate Enrollment)	0.75 ***	0.75 ***
	(0.141)	(0.141)
Constant	-11.87 **	-16.73 ***
	(3.772)	(3.934)
Observations	415	415
R^2	0.33	0.33
F Statistic	199.72 ***	199.72 ***
Note: Robust standard errors in parentheses.		*p<0.1; **p<0.05; ***p<0.01

These results offer two important pieces of insight. Through the (i) interaction term, we can see the *effect on an effect*. This means that we can observe the effect of an institutional characteristic (dummy variable, i.e. city or private) *on* the effect of aid on enrollment. The (ii) coefficients on the dummies and log(Total Aid) variables must be interpreted differently, however. They describe the expected change in log(First ISE) with one percentage change in log(Total Aid), conditional on Dummy = 0. That means that if the institution is *not* located in a city (City = 0), they can expect a 3.8% enrollment increase from a 10% increase in aid, all else equal. Distinguishing between those two parts of the interpretation is crucial. While the coefficients on the dummy variables support the findings of Bicak and Taylor (2020) to an extent, I do not interpret them in further detail. That is because Bicak and Taylor (2020) offer a more reliable analysis of these time-invariant characteristics, owed to a significantly larger sample.

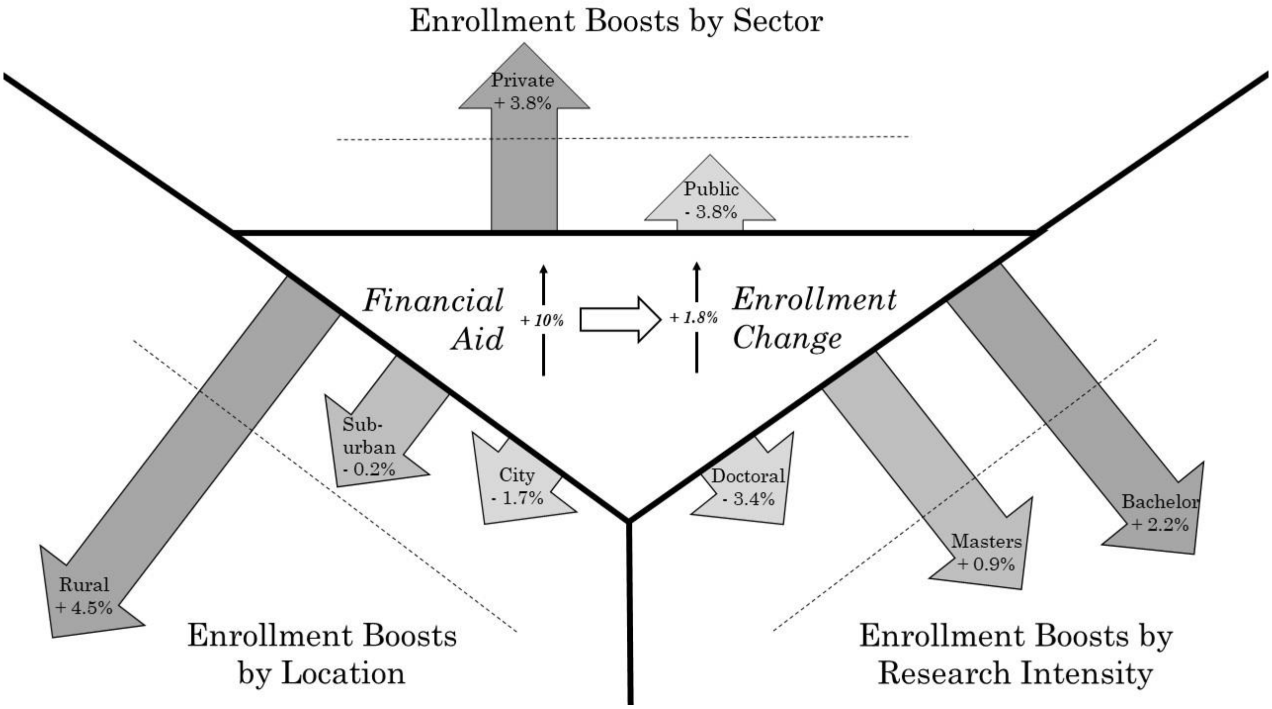
When looking at location-specific characteristics, we see that the Town/Rural model is highly significant. It suggests that universities that are located in a rural area, experience an additional 4.5% enrollment effect when compared to non-rural institutions. This suggests that aid results in an additional enrollment boosts at universities that possess this characteristic. 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 refer to an enrollment decrease, just to a less powerful increase. 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.

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

Table 5 continues this narrative, seeing that public schools have a higher baseline of international students to begin with (Bicak and Taylor, 2020). It is private schools, however, that can really boost their ISE by awarding aid.

The tables resonate existing narratives of attractive institutional profiles, supporting the findings of Bicak and Taylor. I do, however, find that universities that do *not* have inherent attractive qualities experience additional enrollment boosts when they award aid, all else equal. This is an important, even unexpected, insight. We see that aid can compensate for a lack of the most desirable institutional characteristics; namely an urban location, high research activity, situated in the public sector. This insight offers an opportunity for institutions with less attractive profiles to harness the power of financial aid to its fullest potential. As a visual summary, Figure 2 below illustrates the key findings of Section 3.2.

Figure 2: Enrollment Boosts by Sector, Location, and Research Intensity.



4. Discussion and Conclusion

As the first study using CDS data to measure the effect of aid on ISE quantitatively, I find that both total aid and aid concentration have a significant effect on first-time international student enrollment. When contrasting financial aid to other enrollment management measures, I find that aid and its concentration are the only significant and reliable predictors of ISE[14]. In contrast to other measures, i.e. total undergraduate enrollment or acceptance rate, I conclude that financial aid is amongst the most effective, fastest and cheapest ways to incentivize ISE.

This study builds strongly upon the findings of Bicak and Taylor (2020). They examine institutional characteristics, both time-variant and time-invariant, that predict ISE. My study refines their findings with unique data on institutional aid for international students, provided by the CDS. In addition to finding a strong, positive relationship between total aid, its concentration, and first-time ISE, I make a recommendation for different types of institution. While urban, research-intensive, public institutions are attractive destinations for international students, their counterparts can make the most out of awarding financial aid to international

[14] The only significant time-variant predictors.

students. I find that, on average, non-urban, less research-intensive, private universities experience an additional enrollment effect when awarding a fixed amount of aid.

In addition to the institutional perspective, aid is a crucial factor for international students' wellbeing. 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, aid contributes to increasing equity in the educational process. Thus, aid improves the outcome among aided students in addition to making college more accessible and affordable.

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.

I conclude that aid is not only a powerful tool for institutions, but also a necessary support mechanism for international students themselves. Regarding the U.S. economy, international students bring skills and creativity that contribute to innovation and economic growth (Florida, 2007; Tremblay, 2005). According to IIE (2014) calculations, these contributions resulted in over $27 billion of added economic value to the U.S. economy in 2013/2014 alone.

This study manifests financial aid as a mutually beneficial tool to support international students and institutions. The author hopes that this insight can guide policymakers as they strive to revitalize international student enrollment in the future.

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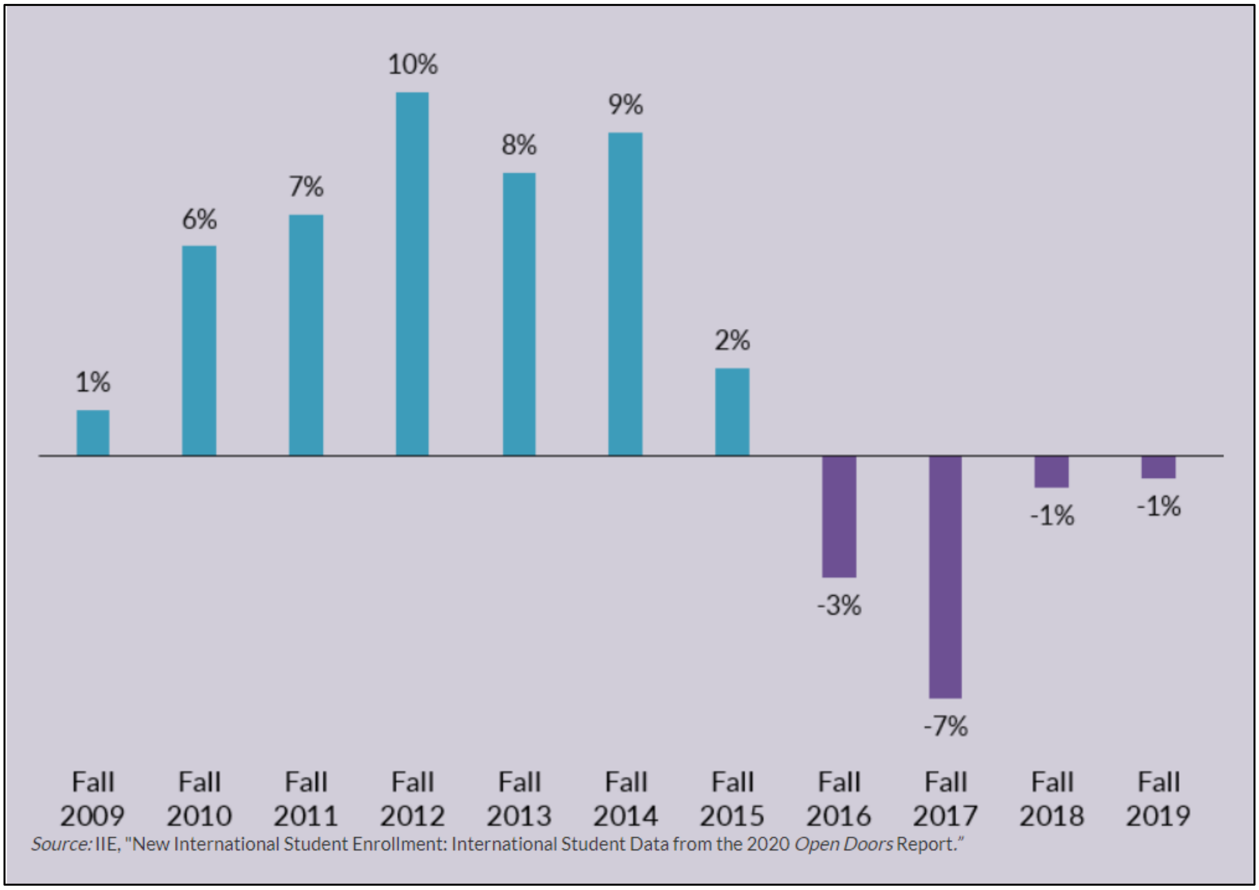
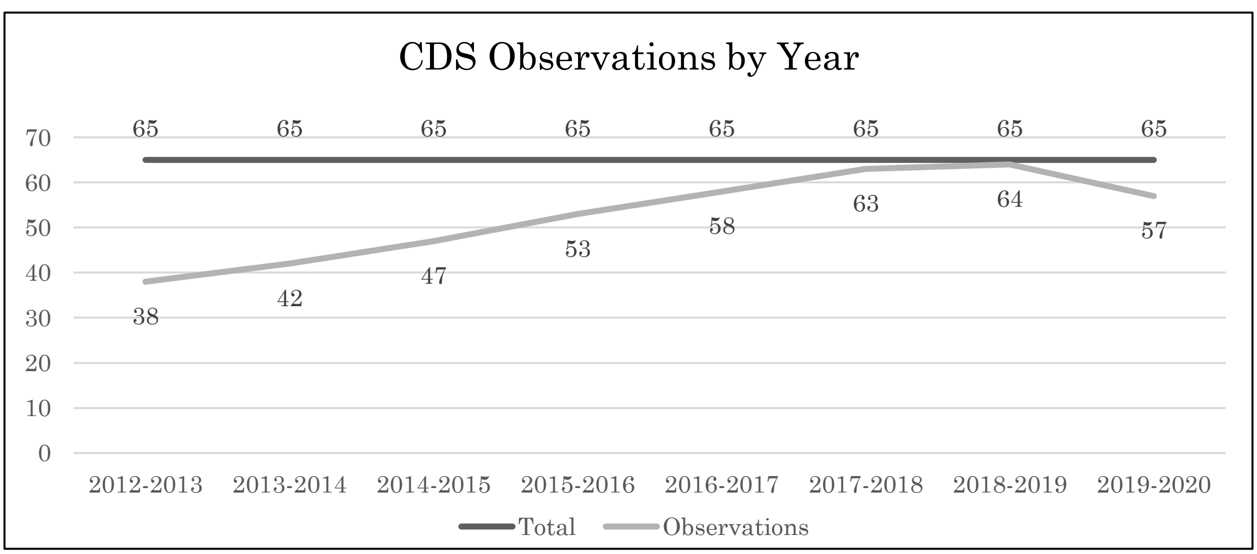
Appendix

Appendix A: ISE Rates since Fall 2009.



Appendix B: CDS Observations by year; using the total aid variable.



Appendix C: Results from OLS, RE models compared to the preferred FE model (3).

	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.			*p<0.1; **p<0.05; ***p<0.01

Note on 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, research, and sector respectively. Let n be defined as the number of binary variables relating to location, research, and sector, respectively.

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- The Kautz-Uible Women in Economics Initiative, which provides scholarships and mentoring to economics students;
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