Predicting International Student Enrollment by Institutional Aid

Using Fixed and Random Effects

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Background

Motivation

Since the fall of 2015, first-time International Student Enrollment (henceforth: ISE_{ft}) has declined for the first time in decades. But why?

1. Political Climate: The "Trump Effect" [Hacker and Bellmore, 2020]
2. Administrative Hurdles: Immigration Challenges [Shih, 2016]
3. ...

International students constitute a vital part of the U.S. campus communities and workforce. Therefore, universities must better understand how to reverse this trend and by incenting ISE_{ft}.

→Financial aid constitutes a promising solution - but little research addresses the relationship between financial aid and ISE_{ft}.

Research Design

This paper uses international student aid and enrollment data from the Common Data Set (CDS), as well as the IPEDS database (National Center for Education Statistics [NCES]).

Moreover,

- Data are sampled from institutions located within the Great Lakes region (OH, IN, IL, MI, WI).
- This study gives rise to a continuous treatment DiD scenario. However, causality could not be established due to treatment effect heterogeneity. [Callaway et al., 2021]
- Results must be interpreted strictly from the institutional perspective: To what extent do changes in aggregate aid awards predict the variation in overall enrollment?

Empirical Strategy

Predicting ISE_{ft} by Institutional Aid

How does financial aid predict ISE_{ft}? Answering this question necessitates addressing three main concerns:

1. Heterogeneity amongst institutions (e.g., size and enrollment)
   →Normalization to log-log framework, see [Bicak and Taylor, 2020]
2. Confounders/ Covariates
   →Incorporate existing financial aid research, see [Cantwell, 2019],[Dynarski, 2000]
3. Institutional and Time Fixed Effects
   →Two-Way Fixed Effects (TWFE) Model, see [De Chaisemartin and d'Haultfoeuille, 2020]

Model Specification

This yields a TWFE model such that

$$Y_{i,t} = \alpha + \hat{\beta} X_{i,t} + \hat{\delta} T_t + \hat{\gamma} F_i + \epsilon_{i,t}. \tag{1}$$

with two variables of interest and three control variables ($\rightarrow X_{i,t}$):

- **log of total aid**: Aggregate aid to all international students
- **aid concentration**: Aid recipients divided by Total ISE_{ft}
- log of total cost: Important in relationship with aid, see [Bodycott, 2009], [Darby, 2015]
- acceptance rate: Proxies for perceived attractiveness, see [Bodycott, 2009], [Darby, 2015], [Mazzarol and Soutar, 2002]
- log of undergraduate enrollment: Proxies for size, see [Cantwell, 2019]

Assessing aid within different institutional settings

Does aid predict ISE_{ft} differently within different institutions? The short answer, probably! Why? We have already concluded that the institutional setting is highly heterogeneous. Therefore, aid is likely to be more or less powerful within certain institutional settings!

Extending the findings of [Bicak and Taylor, 2020], this paper limits this analysis to three dimensions of institutional characteristics:

Table 1: Categories of time-invariant institutional characteristics.

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

Model Specification

Unfortunately, the time-invariance of these three institutional dimensions disqualifies a TWFE approach. This yields an important alternative to the TWFE model: A Random Effects (RE) model[1]:

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

where $Y_{i,t}$ is the logged new ISE_{ft} of institution i in year t. $\hat{\nu}_{i,t}$ 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) established in regression (1).

[1] see [Bell et al., 2019], [Bell and Jones, 2015]

Findings

Predicting ISE_{ft} by Institutional Aid

Relationship between ISE_{ft} and Institutional Aid

A 10% increase in total aid, correlates with a 1.8% increase in ISE_{ft}, all else equal.

Moreover,

- Financial aid is only a significant predictor in conjunction with aid concentration (negative coefficient): This is evidence for the cost barriers that international students face, see [Redden, 2015]
- Financial aid and aid concentration are the most significant (time-invariant) predictors of ISE_{ft}

Full results are reported in the Appendix.

Aid effectiveness within different institutional settings

Relationship between institutional setting and aid effectiveness

Aid effectiveness varies significantly. Aid is an especially powerful predictor of ISE_{ft} in rural, low research, and private universities.

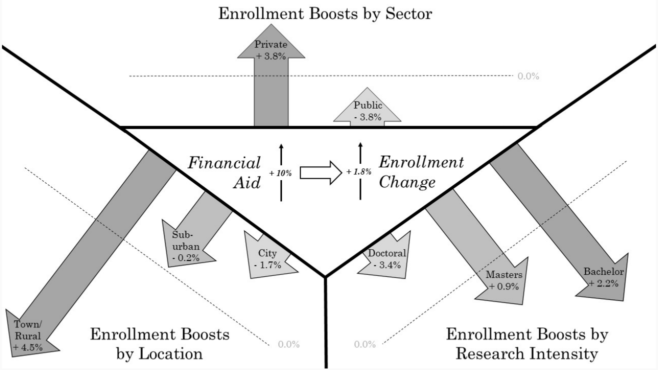

Figure 1: Enrollment boosts by different institutional characteristics.

Implications for Policy and Practice

Implications for Institutions

I find that institutional aid and its concentration are the most significant predictors of ISE_{ft}. Moreover, aid is a more powerful predictor of ISE_{ft} at rural, low research, and private universities. International students affect economic growth and development [Tremblay, 2005] **So what does that mean?**

1. **Institutions**
   - Aid attracts international students, they attract renown and funding for the institutions [McCormack, 2007],[Chellaraj et al., 2008]
   - Aid is a student-centric enrollment tool: It is 'win-win' tool for both students and institutions [Mause, 2009]
   - Less attractive universities (e.g., rural) can use the aid-induced enrollment boosts to compete more effectively (e.g., an internalization strategy per [Knight, 2004])

Implications for Policy

2. Policy

- Award aid to make education accessible to low-income students [Alon, 2009]
- Aid is an effective and reliable tool to attract and retain international talent for policymakers [Douglass and Edelstein, 2009], [Li, 2017]
- Aid to international students can be used as a tool to affect economic development/ growth in certain regions/ industries via universities as intermediaries [Owens et al., 2011]

→**Conclusion:** Financial aid is a reliable enrollment management tool that prioritizes students, institutions, and economic interests!

Thank you! Questions?

Appendix A: FE Regression Specifications

Table 1: Results from the Fixed Effects Model

	Dependent variable:		
	log(First Enrollment)		
	(1)	(2)	(3)
log(Total Aid)	0.18	0.18	0.18
	(0.05)	(0.05)	(0.05)
	$p = 0.0002$	$p = 0.0002$	$p = 0.0002$
Aid Concentration	−0.91	−0.91	−0.85
	(0.22)	(0.22)	(0.22)
	$p = 0.0001$	$p = 0.0001$	$p = 0.0002$
log(Total Cost)	−0.58	−0.52	−0.85
	(0.44)	(0.45)	(0.47)
	$p = 0.20$	$p = 0.25$	$p = 0.07$
Acceptance Rate		0.55	0.47
		(0.44)	(0.44)
		$p = 0.22$	$p = 0.29$
log(Udgr. Enrollment)			1.01
			(0.43)
			$p = 0.02$
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:			*p<0.1; **p<0.05; ***p<0.01

Appendix B: OLS vs. RE vs. FE Specifications

Equation 1: OLS (1), RE (2), and FE (3) models in comparison

	Dependent variable:		
	log(First Enrollment)		
	(1)	(2)	(3)
log(Total Aid)	0.37	0.26	0.18
	(0.03)	(0.04)	(0.05)
	$p = 0.00$	$p = 0.00$	$p = 0.0002$
Aid Concentration	−1.47	−1.20	−0.85
	(0.19)	(0.20)	(0.22)
	$p = 0.00$	$p = 0.00$	$p = 0.0002$
log(Total Cost)	2.04	1.01	−0.85
	(0.27)	(0.30)	(0.47)
	$p = 0.00$	$p = 0.001$	$p = 0.07$
Acceptance Rate	−0.46	0.04	0.47
	(0.28)	(0.39)	(0.44)
	$p = 0.11$	$p = 0.93$	$p = 0.29$
log(Udgr. Enrollment)	0.64	0.61	1.01
	(0.09)	(0.11)	(0.43)
	$p = 0.00$	$p = 0.00$	$p = 0.02$
City	0.61		
	(0.10)		
	$p = 0.00$		
Suburban	0.13		
	(0.11)		
	$p = 0.25$		
Doctoral	−0.96		
	(0.17)		
	$p = 0.0000$		
Masters	−0.98		
	(0.12)		
	$p = 0.00$		
Private	−0.94		
	(0.20)		
	$p = 0.0000$		
Constant	−27.07	−15.45	
	(2.77)	(3.46)	
	$p = 0.00$	$p = 0.0000$	
Observations	415	415	415
R^2	0.78	0.27	0.09
Residual Std. Error	0.72 (df = 404)		
F Statistic	143.04*** (df = 10; 404)	150.22***	6.50*** (df = 5; 338)
Note:			*p<0.1; **p<0.05; ***p<0.01

Appendix C: RE Specification: Location-specific interactions

Equation 2: Location-specific interaction terms

	Dependent variable: log(First Enrollment)		
	(1)	(2)	(3)
City	2.58		
	(0.97)		
	$p = 0.01$		
Suburban		0.11	
		(1.01)	
		$p = 0.92$	
Town/Rural			−6.34
			(1.49)
			$p = 0.0001$
log(Total Aid)	0.36	0.26	0.21
	(0.06)	(0.05)	(0.04)
	$p = 0.00$	$p = 0.0000$	$p = 0.0000$
Aid Concentration	−1.21	−1.18	−1.14
	(0.20)	(0.20)	(0.20)
	$p = 0.00$	$p = 0.00$	$p = 0.00$
log(Total Cost)	1.06	1.01	0.87
	(0.29)	(0.30)	(0.29)
	$p = 0.0004$	$p = 0.001$	$p = 0.004$
Acceptance Rate	0.11	0.05	−0.03
	(0.38)	(0.39)	(0.38)
	$p = 0.78$	$p = 0.91$	$p = 0.93$
log(Udgr. Enrollment)	0.61	0.61	0.68
	(0.10)	(0.11)	(0.11)
	$p = 0.00$	$p = 0.00$	$p = 0.00$
City*log(Total Aid)	−0.17		
	(0.07)		
	$p = 0.02$		
Suburban*log(Total Aid)		−0.02	
		(0.07)	
		$p = 0.76$	
Town/Rural*log(Total Aid)			0.45
			(0.11)
			$p = 0.0001$
Constant	−17.59	−15.52	−13.96
	(3.51)	(3.45)	(3.44)
	$p = 0.0000$	$p = 0.0000$	$p = 0.0001$
Observations	415	415	415
R^2	0.29	0.27	0.30
F Statistic	168.21***	152.30***	172.38***
Note:		*p<0.1; **p<0.05; ***p<0.01	

Appendix D: RE Specification: Research-specific interactions

Equation 2: Research-specific interaction terms

	Dependent variable: log(First Enrollment) (1)	(2)	(3)
Doctoral	5.19		
	(1.01)		
	$p = 0.0000$		
Masters		−2.10	
		(1.08)	
		$p = 0.06$	
Bachelor			−1.96
			(1.02)
			$p = 0.06$
log(Total Aid)	0.40	0.21	0.20
	(0.05)	(0.04)	(0.04)
	$p = 0.00$	$p = 0.0000$	$p = 0.0000$
Aid Concentration	−1.28	−1.17	−1.30
	(0.20)	(0.20)	(0.20)
	$p = 0.00$	$p = 0.00$	$p = 0.00$
log(Total Cost)	0.73	0.67	0.98
	(0.30)	(0.30)	(0.28)
	$p = 0.02$	$p = 0.03$	$p = 0.0005$
Acceptance Rate	−0.05	−0.002	0.05
	(0.37)	(0.38)	(0.37)
	$p = 0.90$	$p = 1.00$	$p = 0.90$
log(Udgr. Enrollment)	0.45	0.55	0.93
	(0.14)	(0.10)	(0.12)
	$p = 0.001$	$p = 0.0000$	$p = 0.00$
Doctoral*log(Total Aid)	−0.34		
	(0.07)		
	$p = 0.0000$		
Masters*log(Total Aid)		0.09	
		(0.08)	
		$p = 0.27$	
Bachelor*ln(Total Aid)			0.22
			(0.07)
			$p = 0.002$
Constant	−13.16	−10.31	−17.48
	(3.78)	(3.57)	(3.25)
	$p = 0.0005$	$p = 0.004$	$p = 0.0000$
Observations	415	415	415
R^2	0.32	0.32	0.35
F Statistic	196.32***	192.85***	223.90***
Note:			*p<0.1; **p<0.05; ***p<0.01

Appendix E: RE Specification: Sector-specific interactions

Equation 2: Sector-specific interaction terms

	Dependent variable:	
	log(First Enrollment)	
	(1)	(2)
Private	−4.86 (1.10) $p = 0.0000$	
Public		4.86 (1.10) $p = 0.0000$
log(Total Aid)	0.15 (0.05) $p = 0.002$	0.53 (0.07) $p = 0.00$
Aid Concentration	−1.21 (0.20) $p = 0.00$	−1.21 (0.20) $p = 0.00$
log(Total Cost)	0.65 (0.36) $p = 0.08$	0.65 (0.36) $p = 0.08$
Acceptance Rate	0.33 (0.38) $p = 0.39$	0.33 (0.38) $p = 0.39$
log(Udgr. Enrollment)	0.75 (0.15) $p = 0.0000$	0.75 (0.15) $p = 0.0000$
Private*log(Total Aid)	0.38 (0.08) $p = 0.0000$	
Public*log(Total Aid)		−0.38 (0.08) $p = 0.0000$
Constant	−11.87 (3.62) $p = 0.002$	−16.73 (3.75) $p = 0.0000$
Observations	415	415
R^2	0.33	0.33
F Statistic	199.72***	199.72***
Note:	*p<0.1; **p<0.05; ***p<0.01	

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