Selling the American Dream: The Effect of Advertising on Enrollment at Less-Selective Colleges

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Disclaimers and Acknowledgments

1. Disclaimer: The content of this presentation is the researcher's own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researcher and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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3. Media Statement: Findings are preliminary, so please do not record, disseminate, cite, or share on social media, including on Twitter.

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Research question:

What is the effect of advertising on demand for college?

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- Effects of own *and* rival ads

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Theory-informed identification: Exploit exogeneity embedded in TV advertising: Advertisers are unable to precisely predict viewership

→ Use control function to absorb the endogenous part of realized TV views or impressions

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Contributions

1. First to estimate effects of own and rival advertising on enrollment
2. New way to identify effect of TV adv on demand w/o policy variation
   + Generalizable to other settings, allows identification of rival effects

Empirical Approach

Identifying the Effect of Advertising on Demand for College

Advertising is a choice by firms, likely correlates w/ unobserved demand

Credible approaches in the literature:

+ Border design: Good identification, but infeasible with current data
+ Political IV: Good strategy for own effects, but rival effects not identified

My approach:

+ Insight: Given an ad spot, advertisers expect a certain # of views, but they always face uncertainty (i.e., realized impressions is stochastic)
+ Idea: Exploit the deviations between expected and realized viewership
+ Key assumption: Factors that shift the viewership of an institution's ads are uncorrelated with other determinants of its enrollment

Naive Model

Let j =institution, t =year

$$y_{jt} = \psi + \boldsymbol{a}'_{jt}\beta + \boldsymbol{x}'_{jt}\gamma + \rho_j + \tau_t + u_{jt} \tag{1}$$

- y_{jt}= j's new enrollment in year t
- $\boldsymbol{a}'_{jt} = \begin{bmatrix} a_{jt} & a_{-jt} \end{bmatrix}$ = own and rival TV impressions
- $\boldsymbol{x_{jt}}$ = time-varying college attributes
- ρ_j = unobserved institutional features/student tastes for j
- τ_t = aggregate/common shocks to college enrollment in t
- u_{jt} = mean zero error
- β is the parameter of interest

Empirical Strategy

Step 1: Use ad spending s_{jt} to form a prediction of impressions $\hat{a}_{jt}$

$$\hat{a}_{jt} = f(s_{jt})$$

Assumption: $\hat{a}_{jt}$ captures all predictable variation in a_{jt} (when ads purchased)

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Step 2: Use the predicted impressions in a control function $C(\hat{a}_{jt})$ to isolate exogenous variation in realized impressions

Estimating equation:

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Intuition: $C(\hat{\mathbf{a}}_{jt})$ controls for the part of $\mathbf{a}_{jt}$ that correlates with u_{jt}, so the remaining component of the error, ε_{jt}, is uncorrelated with $\mathbf{a}_{jt}$.

β is identified if $E(\varepsilon_{jt}|\mathbf{a}_{jt}, C(\hat{\mathbf{a}}_{jt}), \mathbf{x}_{jt}, \theta_j, \sigma_t) = 0$

Data and Descriptive Statistics

College and Advertising Data

College Data: IPEDS Title IV undergraduate-serving institutions 2010-15

- Key variables: Fall new enrollment (outcome), prior year tuition, ave. instructional spend, majors offered
- Restrict to less-selective public/private (admit ≥80%, no test/GPA requirements), community/tech, and for-profit colleges

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Annual county economic data: To control for variation in local college demand

Sample Statistics - Institution Characteristics

	Publics			For-Profits			All Insts		
	Non – Adv	*Adv*	*All*	*Non – Adv*	*Adv*	*All*	*Non – Adv*	*Adv*	*All*
Fall Undergraduates	8,591	13,359	9,701	324	1,434	708	1,851	2,807	2,159
	(7,983)	(12,879)	(9,565)	(905)	(9,015)	(5,378)	(4,761)	(10,099)	(6,962)
Fall New Enrollments	2,149	3,131	2,377	115	325	187	489	650	541
	(1,925)	(3,038)	(2,271)	(297)	(1,379)	(852)	(1,172)	(1,868)	(1,436)
Tuition and Fees	3,309	3,737	3,409	13,340	16,967	14,595	11,514	15,254	12,721
	(2,414)	(1,662)	(2,268)	(5,997)	(5,714)	(6,147)	(6,864)	(6,906)	(7,096)
Instruct. Spend/Student	4,205	3,798	4,110	5,610	4,920	5,375	5,946	5,357	5,758
	(3,539)	(1,918)	(3,240)	(5,728)	(4,200)	(5,269)	(9,196)	(8,391)	(8,951)
Student-Faculty Ratio	22	21	22	16	22	18	17	22	18
	(8)	(7)	(7)	(8)	(11)	(9)	(8)	(10)	(9)
Offers Weekend/Evening Class (%)	63	70	65	43	65	50	46	66	53
	(48)	(46)	(48)	(49)	(48)	(50)	(50)	(47)	(50)
Offers Distance Education (%)	86	96	88	12	42	23	27	49	34
	(35)	(20)	(33)	(33)	(49)	(42)	(45)	(50)	(47)
Retention Rate (FT)	64	60	63	73	63	69	71	63	68
	(13)	(12)	(13)	(19)	(21)	(20)	(19)	(20)	(20)
Observations	2,006			9,572			12,327		

Sample Statistics - Advertising

	2-Year Publics Mean/SD.	2-Year For-Profits Mean/SD.	4-Year Publics Mean/SD.	4-Year For-Profits Mean/SD.	Private Non-Profits Mean/SD.	All Mean/SD.
Own TV Ad Spend (000)	81	321	378	434	180	332
	(177)	(459)	(1,225)	(479)	(273)	(486)
Own GRPs	161	867	509	939	371	792
	(319)	(1,122)	(1,353)	(1,139)	(473)	(1,088)
# TV Ads	391	3,029	648	2,677	1,063	2,502
	(603)	(3,782)	(1,521)	(3,396)	(1,723)	(3,453)
Own TV Ads Duration (hours)	3	26	5	29	9	24
	(5)	(33)	(12)	(35)	(15)	(32)
# Rivals Advertising	21	26	17	27	22	25
	(11)	(16)	(14)	(15)	(13)	(15)
Rival TV Ad Spend (000)	6,620	9,123	5,737	9,251	7,478	8,764
	(5,059)	(9,213)	(6,025)	(8,153)	(7,196)	(8,424)
Rival GRPs	14,603	17,876	13,667	19,127	15,687	17,782
	(10,601)	(11,451)	(13,567)	(10,904)	(10,644)	(11,301)
Observations	374	1,942	101	1,367	199	3,983

Results

Effect of Own and Rival GRPs on Enrollment

	Percent Effect on New Enrollment	
	Units: 100 GRPs	*Units:* 1 SD GRPs
Own GRPs	1.22***	8.75***
	(0.25)	(1.77)
Rival GRPs	0.01	1.05
	(0.01)	(1.65)
Ave Enrollment	547	
Inst-Year Obs	12,559	
Unique Insts	2,439	

Own-Advertising Elasticities by Control

	Effects of Own Advertising		
Advertiser Control			
Publics	0.058***	(0.018)	[0.022, 0.093]
Private Non-Profits	0.012	(0.064)	[−0.113, 0.138]
For-Profits	0.111***	(0.023)	[0.066, 0.157]
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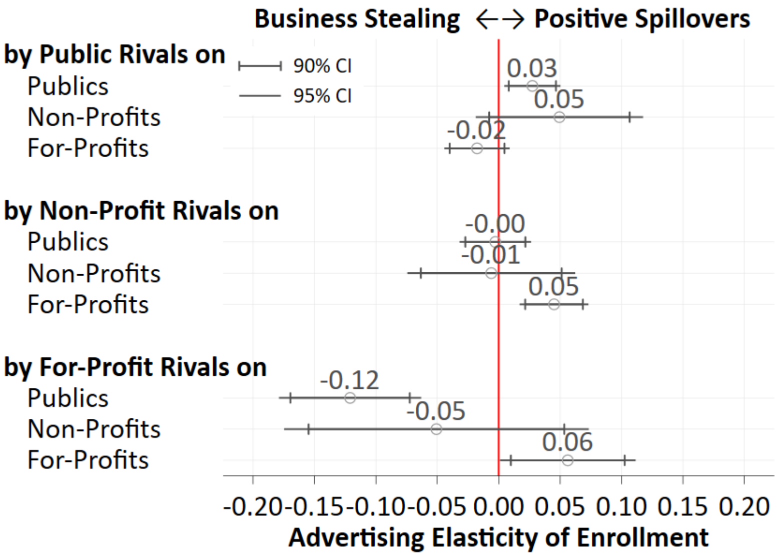
Cross-Control Effects of Rival Advertising



Cross-Sector Rival Elasticities

	on New Enrollment at				
Effect of GRPs by	2 Year Publics	2 Year For-Profits	4 Year Publics	4 Year For-Profits	All Private Non-Profits
2 Year Publics	0.017	0.003	−0.044	0.000	0.021
	(0.015)	(0.017)	(0.051)	(0.035)	(0.036)
2 Year For-Profits	−0.101	0.028	−0.032	0.083	−0.016
	(0.029)	(0.025)	(0.047)	(0.057)	(0.062)
4 Year Publics	0.023	−0.021	0.068	−0.060	0.077
	(0.022)	(0.022)	(0.028)	(0.057)	(0.052)
4 Year For-Profits	−0.036	−0.006	−0.070	0.135	−0.005
	(0.018)	(0.019)	(0.060)	(0.063)	(0.032)
All Private Non-Profits	−0.011	0.045	0.035	0.044	−0.015
	(0.016)	(0.016)	(0.035)	(0.032)	(0.036)
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- But costs could be outweighed by higher degree completion rates

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More research needed to understand how student outcomes affected

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2. Effect of rival advertising differs by the level of institution
   - Among 2 year institutions, evidence of cross-sector business stealing:

     2 year for-profit advertising especially harms community colleges (-0.10)
   - Among 4 year colleges, evidence of w/in sector positive spillovers

     Public on public: 0.06

     For-profit on for-profit: 0.135

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2. Effect of rival advertising differs by the level of institution
   - Among 2 year institutions, evidence of cross-sector business stealing:
     2 year for-profit advertising especially harms community colleges (-0.10)
   - Among 4 year colleges, evidence of w/in sector positive spillovers
     Public on public: 0.06
     For-profit on for-profit: 0.135
3. Ads by private non-profits have insignificant own effect but positive impact on enrollment at for-profit competitors

Stay Tuned - Coming Soon!

Alternative control function: Use rich spot attributes + ML to nonparametrically predict impressions

- Train random forest on ads aired in prior year (all products)
- Leverage detailed data on media type, channel/distributor, TV program name and genre, commercial pod, day of week, and time of day to predict impressions
- Predict impressions separately by demographic group
- Estimate impacts using impressions and enrollment by sex

Comments welcome!

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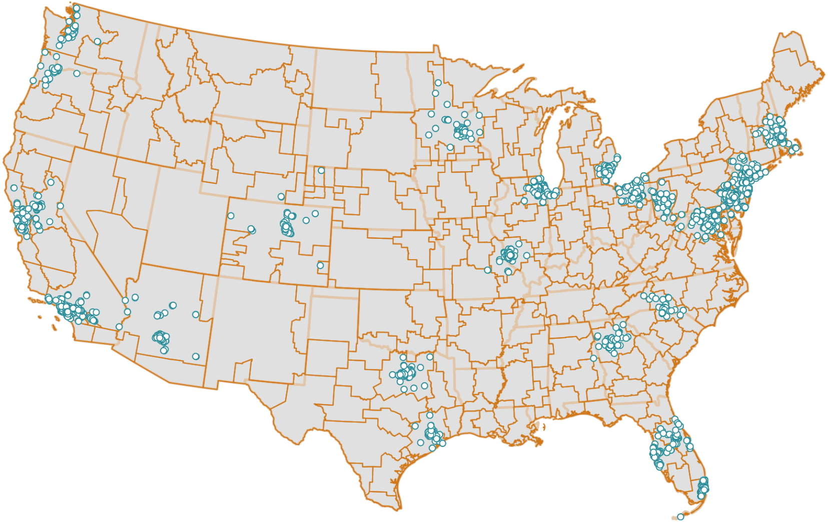
Appendix

The U.S. has 210 media markets known as DMAs



Return

Empirical Strategy (Details)

Identifying the causal effects of advertising on demand

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- Possibility of strategic responses to competing firms
- Unobserved factors affecting both ad choices and college-going

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→ Need exogenous variation in advertising to identify effect on enrollment

Model of college enrollment with advertising

Let j =institution, t =year

$$y_{jt} = \psi + \boldsymbol{a}'_{jt}\beta + \boldsymbol{x}'_{jt}\gamma + \rho_j + \tau_t + u_{jt} \tag{3}$$

where y = new enrollment, $\boldsymbol{a}'_{jt} = \begin{bmatrix} a_{jt} & a_{-jt} \end{bmatrix}$ = own and rival impressions, $\boldsymbol{x}$ = college attributes, ρ_j = student tastes for j, τ_t = aggregate demand shocks, u_{jt} = mean zero error, and β is the estimand

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Identification challenge:

$$E(u_{jt}|\boldsymbol{a}_{jt}, \boldsymbol{x}_{jt}, \rho_j, \tau_t) \neq 0.$$

I need exogenous variation in advertising to identify β

Solution: Exploit unanticipated variation in impressions

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...but realized impressions is stochastic:

$$a_{jt} := \mu_{jt} + \eta_{jt}, \text{ where } \mu_{jt} \perp \eta_{jt}$$

Interpretation: η_{jt} are random fluctuations in TV viewing that cannot be predicted at time of purchase.

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What causes $\eta_{jt} \neq 0$? Traffic jams, weather, March Madness, power outages

I adopt a two-step approach

My strategy is to exploit η_{jt} to identify the effect of impressions on enrollment

Step 1: Predict the impressions that advertisers could expect when ads purchased

Step 2: Use the predicted impressions as a control function, which isolates exogenous variation in realized impressions