Essays on Selection Markets and Contract Design

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My Research

Flexible labor market incentives can improve cost-effectiveness and fairness

- Target people with the largest social benefits
- Without increasing public spending or harming decision-makers

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I extend insights and empirical methods from health insurance to new domains:

- Target new patients to high-capacity physicians
- Target undertreating physicians to strong incentives
- Target high-ability students to selective universities

Common approach:

- Extend prior theory with realistic constraints and mapping to data
- Measure effects of existing policies with administrative data
- Recover underlying structure of preferences and information $\rightarrow$ explore reforms

Chapter 1

Healthcare policy interventions often target low-access communities

- Under-tested “crowd-out" assumption: fewer patients per physician $\rightarrow$ better treatment
- e.g., patient list ceilings, loan forgiveness, salary subsidies

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- Causal evidence is limited and unobserved factors likely matter
- Physicians may choose locations with better patient health
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Research question

What is the effect of a primary care physician’s number of registered patients (“enrollment”) on short-run treatment intensity?

This Paper

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Does enrollment decrease treatment intensity? ▸ Contribution

I instrument for enrollment with quasi-random patient assignments

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Physicians spend less time with incumbent patients

- Economically small effect size, driven by fewer services
- Still corresponds to small increase in avoidable hospitalizations

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Use theoretical framework to distinguish between two mechanisms

- Capacity constraint $\rightarrow$ No spare time, need more physicians
- Income effect $\rightarrow$ Extra effort is costly, need stronger incentive
- Effect heterogeneity most consistent with idiosyncratic capacity constraints

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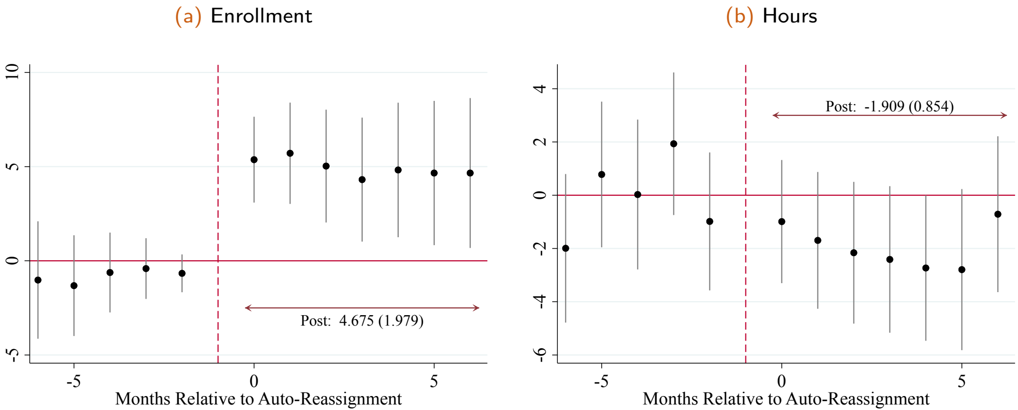
Fixing physician supply, targeted assignment eliminates 86 percent of crowd-out

Identifying Variation: Large Reassignments Increase Enrollment



Notes: I define large auto-reassignments as those with two or more reassigned patients (969 of 2,722 physician-spells). Estimates refer to β_{1t} in the following regression: $Y_{jt} = \beta_{0t} + \beta_{1t}\text{AutoHigh}_j + \beta_j + \epsilon_{jt}$.

▸ Why Norway?

Econometric Model

$$Y_{jt} = \beta_1 \widehat{\text{Enroll}}_{jt} + \beta_j + \beta_t + \epsilon_{jt} \quad (1)$$

$$\text{Enroll}_{jt} = \gamma_1 \text{Auto}_{jt} + \gamma_j + \gamma_t + \varepsilon_{jt} \,. \quad (2)$$

Y_{jt} is the outcome of interest, t months after auto-reassignment

- Sum among incumbent patients of physician j

Enroll_{jt} is total enrollment, including incumbents and newly joined patients

Auto_{jt} reflects the cumulative number of patients auto-reassigned

- Validity: auto-reassigned patients only affect incumbents through enrollment
- e.g., doesn't coincide with missed preventative care or local viral outbreak
- Auto-reassignment size is conditional uncorrelated with physician characteristics

Effect of Enrollment Among Incumbent Patients

	Enrollment (1)	Hours (2)	Bill Lines (3)	Spending (4)	Visits (5)
Cuml. Auto-Joins	1.055				
	(0.055)				
	[<0.001]				
Enrollment		−0.048	−0.345	2.230	0.004
		(0.026)	(0.055)	(4.597)	(0.152)
		[0.070]	[<0.001]	[0.628]	[0.980]
Dep. Var. Mean	1274.917	101.349	1126.464	10299.286	370.160
New Pat. Mean		0.124	1.313	131.205	0.400
F-Statistic	117.129	20.101	30.679	9.458	28.624
Observations	35,386	35,386	35,386	35,386	35,386
	Lines Per Visit (6)	Procedures (7)	Diagnostics (8)	Follow-ups (9)	Avoidable Hosp. (10)
Enrollment	−0.002	−0.038	−0.058	−0.023	0.001
	(0.000)	(0.019)	(0.015)	(0.021)	(0.000)
	[<0.001]	[0.045]	[<0.001]	[0.268]	[0.024]
Dep. Var. Mean	2.940	70.908	270.428	135.084	3.619
New Pat. Mean	3.244	0.096	0.293	0.165	0.004
F-Statistic	36.423	46.320	43.653	26.550	6.869
Observations	34,578	35,386	35,386	35,386	35,386

Heterogeneity and Mechanisms

Crowd-out is concentrated among physicians at capacity

- Model: inconclusive because at-capacity physicians have greater workload

Crowd-out is similar across physicians with different financial incentives

- Model: consistent with binding capacity

Crowd-out is concentrated among part-time physicians

- Model: Inconsistent with symmetric income effects or capacity constraint

Tie-breaker: Does a physician's hours bunch at her maximum over the long-run?

- Occasionally, for part-time physicians

Takeaway: How to reduce crowd-out?

Hiring more full-time physicians may be more cost-effective than higher (part-time) pay

Estimates

Counterfactual: Targeted Patient Assignment

Hiring physicians might still be too expensive for small increases in treatment

- Fixing the set of physicians, can we do better than random patient assignment?

Target physician-patient assignments with low crowd-out

- Estimate effects for subsamples: old vs. young patients at high- vs. low- crowd-out physicians (high = part-time or near capacity)
- Simulate sequential assignments to nearby physicians, prioritizing lowest crowd-out

Takeaway

86% of crowd-out hours avoided by targeted assignment

Conclusion: Do New Patients Displace Existing Patients' Treatment?

Yes, but the effects are small

- Leverage quasi-random administrative assignment
- Physicians can shift along their labor supply curve without large frictions

Policy implication: high enrollment doesn't necessarily imply low access

- New measures should guide rural subsidies and patient limits
- Important to consider heterogeneous capacity constraints
- Targeted assignment can mitigate negative health impacts

Chapter 2

Central challenge in healthcare: physicians know more than patients and insurers

- How should physicians be reimbursed for treatment?

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- Variable fee ("Fee-For-Service"): may incentivize **over**-utilization $\rightarrow$ wasteful spending
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- But, physicians might be **heterogeneous** → could do better?
- Screening on observed differences may be infeasible or inadequate

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Theory: A physician's **choice of contract** can convey private information

Research question

Should a regulator offer a menu of reimbursement contracts instead of a uniform contract?

Two Contracts **Sometimes** Better Than One

Uniform (Mixed) Contract

Contract 1

$45 per hour
("Fee-for-Service Rate")

$4 per patient
("Base Payment")

Two Contracts **Sometimes** Better Than One

Menu of (Two) Contracts

Contract 1	**Contract 2**
\$45 per hour ("Fee-for-Service Rate")	\$50 per hour ("Fee-for-Service Rate")
\$4 per patient ("Base Payment")	\$1 per patient ("Base Payment")

This Paper

Research Question

Could a menu of reimbursement contracts improve patient health at the same cost? ▸ Contribution

Model: heterogeneous physicians choose **reimbursement contract** and **treatment hours**

- Physicians' private information: altruism, cost of **effort**, and patient need

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- Test for physician heterogeneity with DiD and quasi-random assignment
- Estimate structural model of treatment → distribution of physician parameters
- Derive **budget-neutral** menu of contracts to maximize **perceived** health

Main Empirical Findings

Physicians drive meaningful variation in treatment

- Reduced-form: physician-specific effects span 0.38 standard deviations
- Structural: **correlated** heterogeneity in physician parameters

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Budget-neutral menu **increases** treatment hours by 6% (mean = 11 minutes/month)

- Less under-utilization: low-hours physicians choose high fee-for-service rates
- Physicians **perceive** added benefit to patients of \$0.50 (5% of spending)

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All physicians and >99% of patients would be better off

- Largest gains for patients of physicians with **high opportunity cost** and **low altruism**
- Narrows urban-rural disparity, especially for most severe patients

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Asymmetric information remains quite costly: \$350M per year for full population

- Limited gains from further increasing contract flexibility

Physicians Vary in Multiple Ways

What patterns of physician heterogeneity should be in the empirical model?

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1. When fee-for-service rate increases, PCPs increase treatment hours
   - Stacked differences-in-differences with patient fixed effects
   - Some more than others

     $$Y_{ijt} = \beta_j \left(Post_{jt} \times Certified_j \right) + \boldsymbol{\beta}_x \boldsymbol{X}_{jt} + \gamma_i + \gamma_{y(t)} + \gamma_{m(t)} + \epsilon_{ijt}$$

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2. Some PCPs persistently treat similar patients more intensively than others
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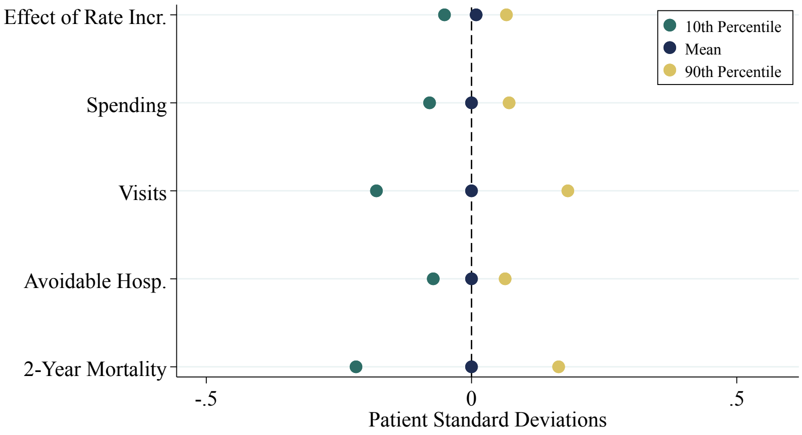
3. PCPs causally affect treatment and adverse outcomes, e.g., two-year mortality
   - Random patient assignment after nearby PCP exits (Ginja et al., 2022)
   - New evidence: dispersed effects on spending and avoidable hospitalizations

     $Y_{ij} = \beta_j + \beta_{j_0(i)} + \beta_x X_j + \epsilon_{ij}$

Dispersion in Physician-Specific Effects

Moving from the 10th to 90th percentile of physicians

- Equivalent to 12-38 percent of a standard deviation across patients
- Bayesian shrinkage adjusts for estimation error



Measuring Physician Heterogeneity

Data: Hours m_{ijt}, Fee-for-Service Rate p_{it}, and X_{it}, for patient i, physician j, month t

- X_{it} includes chronic illness, gender, disability, income, tenure, month, age, and lags

Parameters to estimate:

- Altruism α_j: physicians' responsiveness to increased fee-for-service rate

Estimating Equation

$$m_{ijt} = \max\{0, \tfrac{p_{it}-c_j}{\alpha_j} + \gamma_j \exp\left(\vec{\beta} X_{it} + \sigma\epsilon_{ijt}\right)\} \mid \lambda > 0$$

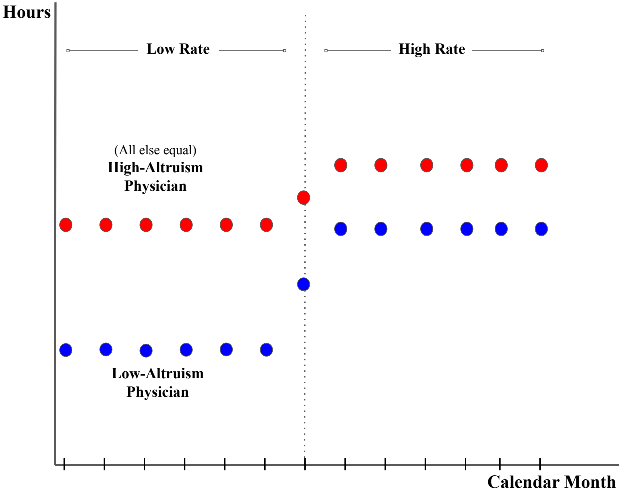
Estimated parameters maximize the likelihood of observed treatment hours

Measuring Physician Heterogeneity

$$\max_{m \equiv \text{Hours}} \ \text{Profit}(m) + \ \textbf{Altruism} \times \text{Health}(m) \quad \Rightarrow \quad \frac{dm}{d\,\text{Rate}} \approx \frac{1}{\text{Altruism}}$$

High-Altruism PCPs Respond Less to Increased Fee-for-Service Rate

Stylized Example with All Else Equal



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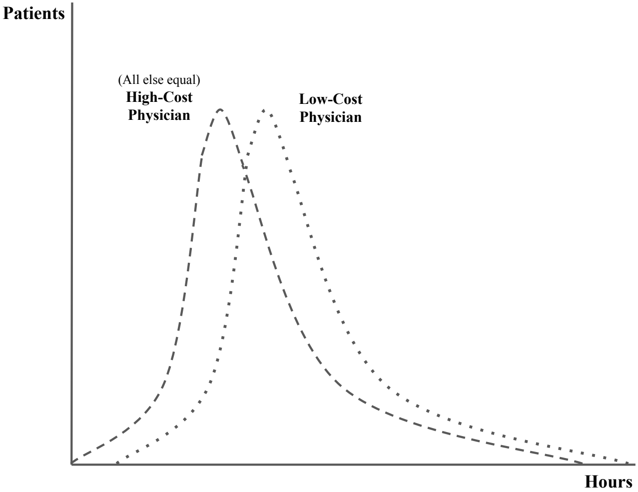
High-Cost PCPs Persistently Treat Additively Less

Stylized Example with All Else Equal



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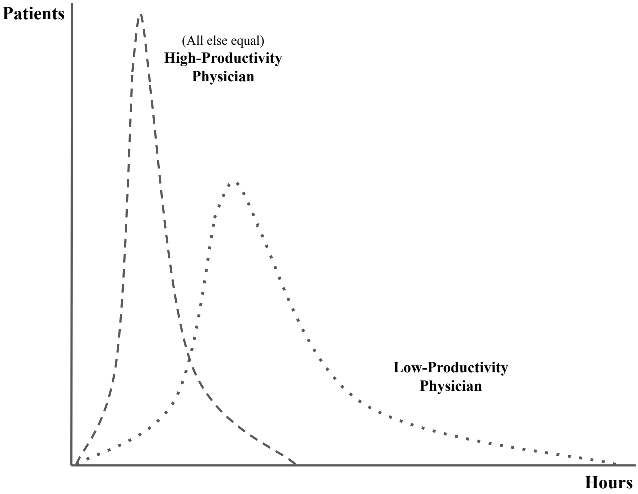
$$\max_{m \equiv \text{Hours}} \ \text{Profit}(m) + \quad \text{Altruism} \times \textbf{Health(m)} \quad \Rightarrow \quad \frac{d \text{ Health}}{d \text{ Productivity}} > 0$$

High-Productivity PCPs Persistently Treat Multiplicatively Less

Stylized Example with All Else Equal



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- Patient Severity $\lambda \sim F(\vec{\beta}, \sigma)$: correlations and variance of residual treatment

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Imperfect Information: a Two-Contract Menu **May** be Preferable

Reference Contract: Best Uniform	\$2.12 + \$55 × m	

Imperfect Information: a Two-Contract Menu **May** be Preferable

Fix both fee-for-service rates

$(x_L$, "Low Rate")	$(x_H$, "High Rate")
\$2.12 + \$55 × m	\$2.12 + **Δb** + **\$56** × m

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Δb = \$0		

Vary the incremental base payment

Imperfect Information: a Two-Contract Menu **May** be Preferable

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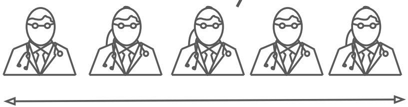
Δb = $0	0%	**100%**



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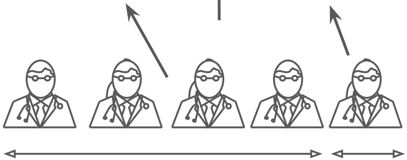
⋮	⋮	⋮
Δb = -$0.07	**7%**	**93%**



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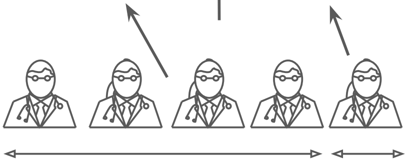

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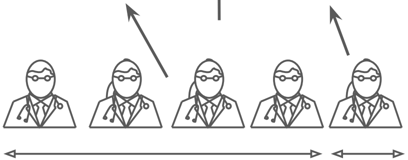
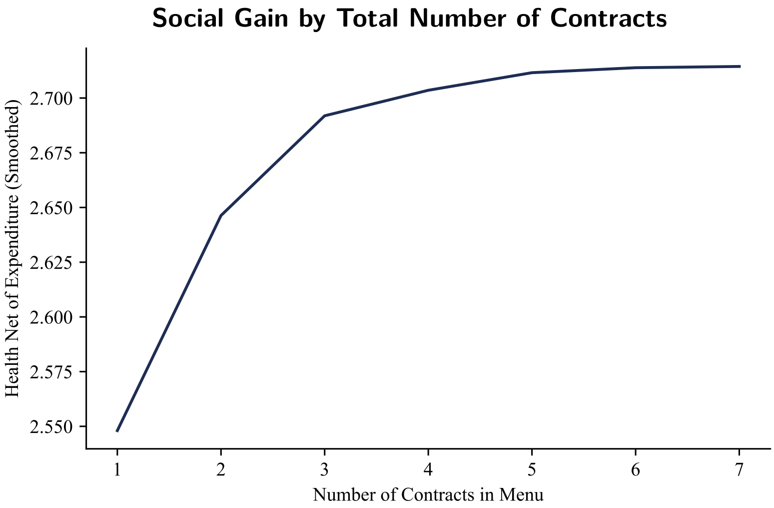


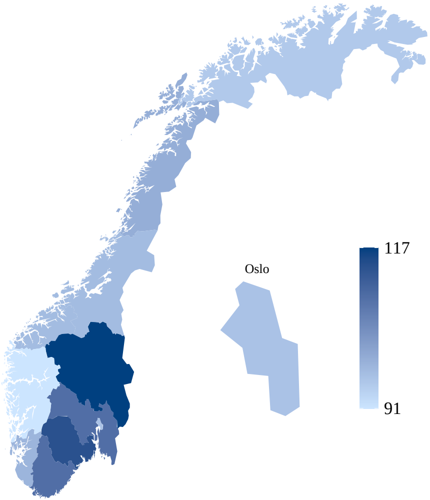
What drives choice? (Private Gain)	Low Patient Severity	High Patient Severity
Is it efficient? Yes! (Health - Expenditure)	Low Cost	High Cost

More Than Two Contracts is Even Better

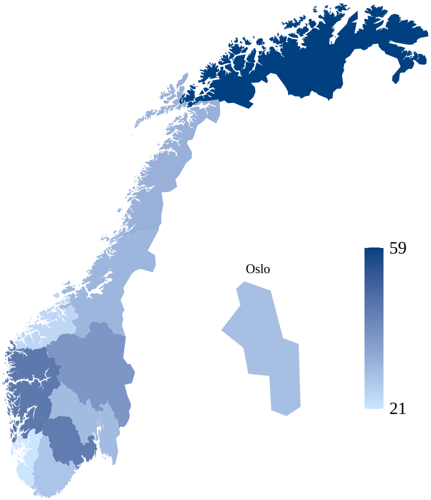


Patients with High Unmet Need Benefit Most

Mean Annual Spending ($)



Annual Health Gain from Menu ($)



Conclusion: Should Physicians Choose Their Reimbursement Rate?

Physicians hold **private information** about their heterogeneity and patients' needs

- Asymmetric information is costly $\rightarrow$ contract choice can **sometimes** help
- **Correlated** heterogeneity helps align private and social gains

Policy implication: a simple, voluntary, budget-neutral menu can improve health

- Recent reform: higher base payments for high-need patients

Other settings might benefit from menu design

- Testable with panel variation in incentives
- Implications for U.S. reforms: value-based care and site-neutral payment
- Uniform flat-fee contracts common in public service

Chapter 3

Some universities are better than others at improving long-run outcomes.

- Dale and Krueger, 2002, 2014; Mountjoy and Hickman, 2021, Ge et al. 2022, Chetty, et al., 2023

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Low match quality with universities/majors can actively hurt students

- \$1.75 billion in student debt and $>$ 50% don't graduate on-time
- Increasing disparities by race, sex, and family income

Chapter 3

Some universities are better than others at improving long-run outcomes.

- Dale and Krueger, 2002, 2014; Mountjoy and Hickman, 2021, Ge et al. 2022, Chetty, et al., 2023

Low match quality with universities/majors can actively hurt students

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Recent policy changes limit the scope for admissions to equitably ration spots

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- California Prop 209 worsened minority students' outcomes (Bleemer, 2021)

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- Internalize students' private information about graduation

Research question

Can selective universities use graduation-contingent loan forgiveness to improve match quality?

This Paper

Research Question

Can graduation-contingent loan forgiveness improve match quality? ▸ Contribution

Identifying variation: loan forgiveness program aimed at increased effort and graduation

- Selection on observables: 12pp higher graduation
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Estimate structural model of admitted students' school choice, loan take-up, and graduation

- First, demonstrate heterogeneous returns to flagship university enrollment
- Why was loan forgiveness ineffective? High app. costs and ignored selection

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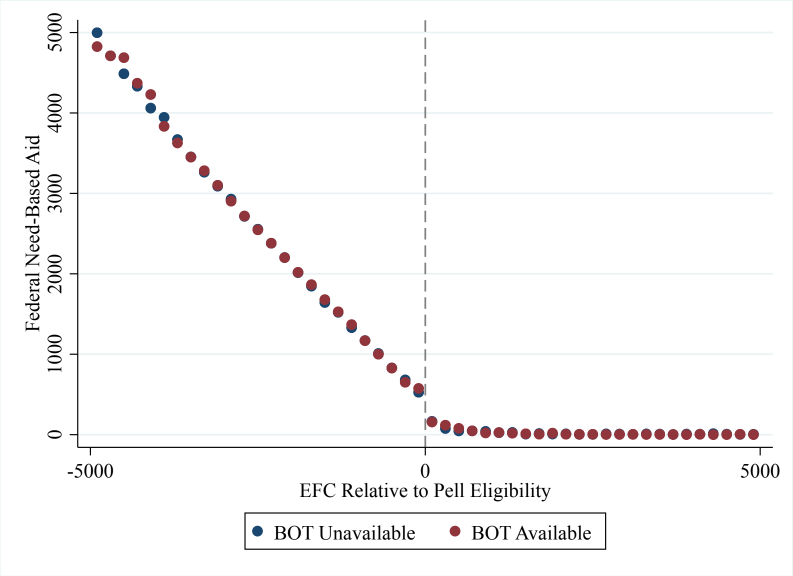
Simulate welfare increase under counterfactual financial aid schedules

- Perfect information: $26,820 per student and 0.55pp higher graduation
- Screening on (more) observables: 80%
- Screening with loan forgiveness 92%

Identifying Variation: Pell Grant Eligibility



Contribution

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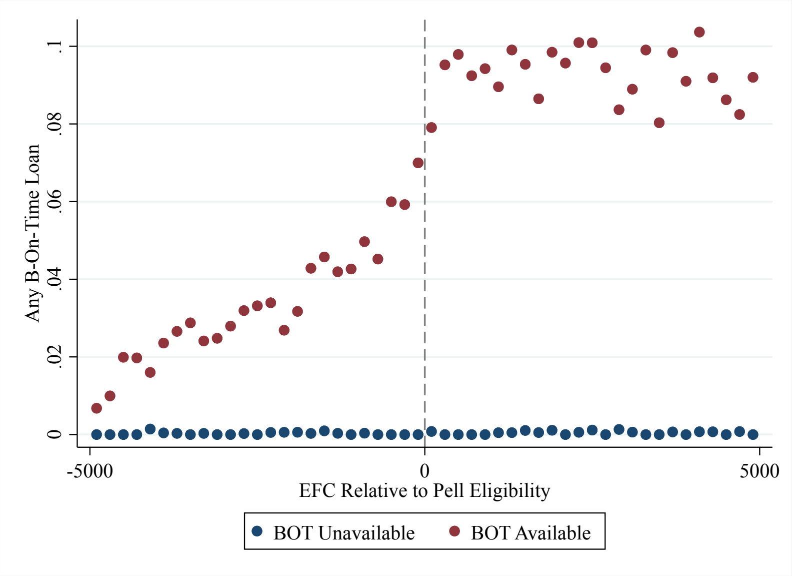

Contribution

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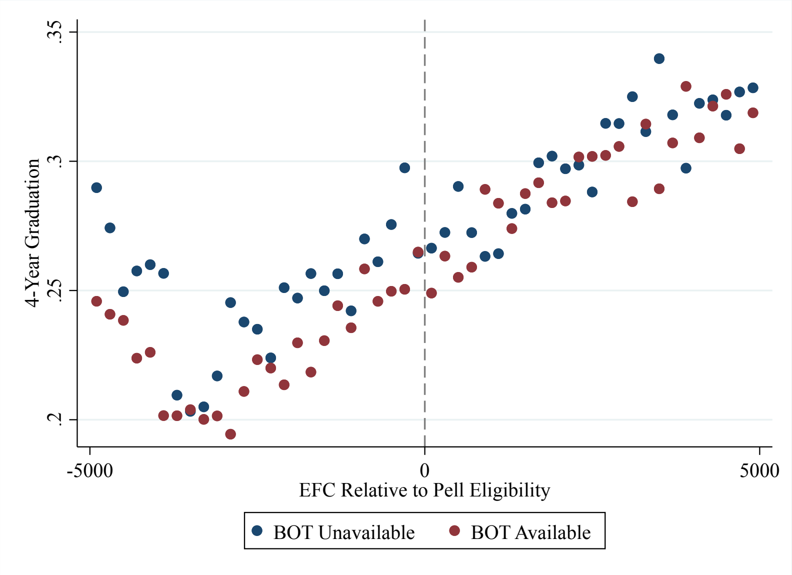

Contribution

Difference-in-Discontinuity: Pell Ineligible × BOT Available

	Estimate	Std. Err.	P-Value	Outcome Mean	R^2	Obs.
Financial Aid						
Federal Aid	0.006	(0.021)	[0.789]	1.661	0.837	256,984
Any B-On-Time Loans	0.030	(0.009)	[<0.001]	0.036	0.102	256,984
Traditional Loans	−0.418	(0.123)	[<0.001]	3.987	0.231	256,984
Net Cost of Attendance	−0.889	(0.196)	[<0.001]	12.115	0.609	256,984

Difference-in-Discontinuity: Pell Ineligible × BOT Available

	Estimate	Std. Err.	P-Value	Outcome Mean	R^2	Obs.
Program Choice						
Enrolled at a Flagship	−0.001	(0.002)	[0.617]	0.169	0.933	256,984
E[Graduation | Major]	0.011	(0.005)	[0.053]	0.288	0.104	256,984
Effect of Major on Earnings	0.029	(0.144)	[0.839]	−0.248	0.043	256,981
Effort Proxies						
Credit Hours Attempted	1.052	(0.974)	[0.281]	68.077	0.587	256,984
Contemporary Employment	0.003	(0.010)	[0.770]	0.759	0.039	256,984
Max Class Rank	0.031	(0.025)	[0.227]	2.301	0.671	256,796
Outcomes						
Graduation Within 4 Years	−0.000	(0.011)	[0.996]	0.243	0.089	256,979
Graduation Within 6 Years	0.032	(0.014)	[0.027]	0.513	0.119	227,552
Earnings After 8-10 Years	1.119	(0.950)	[0.240]	73.061	0.365	256,984

Empirical Model Set-up and Identification

Regulator maximizes student objective plus a fiscal externality

- Fix total enrollment, aid budget, and university objective
- **Universities** care about profit and demographic composition

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Students choose university then BOT

- They care about brand and (idiosyncratic) price, distance, and graduation chance
- Students vary in preferences and uncertain BOT application cost
- Graduation chances vary across both students and flagship vs. other

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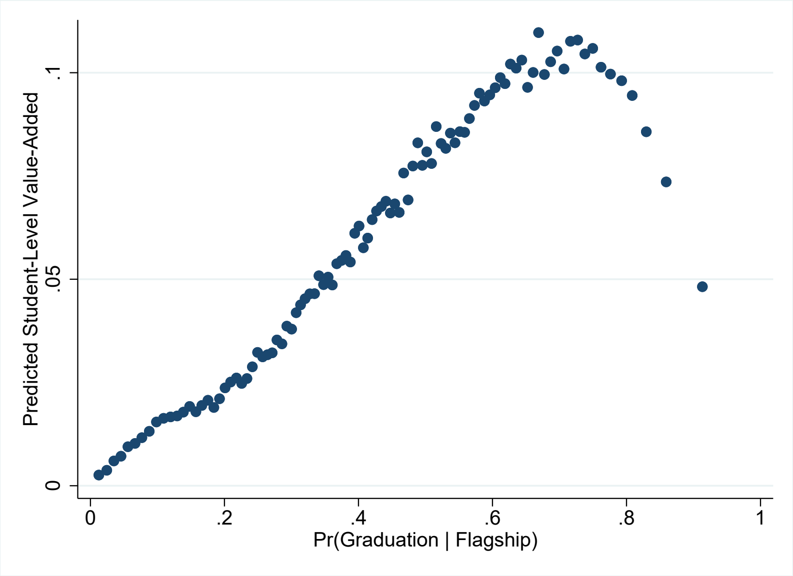
Identification

- BOT take-up among similar students identifies variance in graduation chances
- Remaining differences in graduation identify **average** chances
- Formulaic need-based financial aid identifies price sensitivity
- Remaining differences in college choice identify preference for grad, brand, distance

Predicted Ex-Ante Graduation Likelihood



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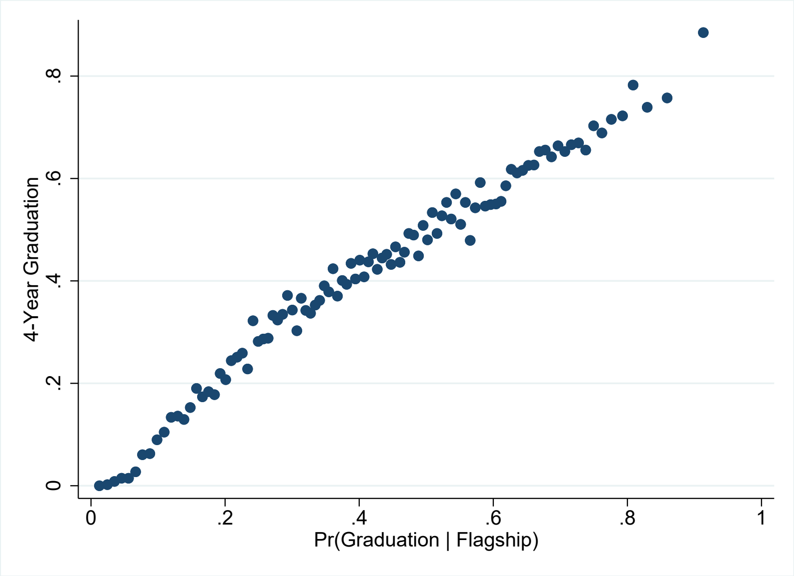

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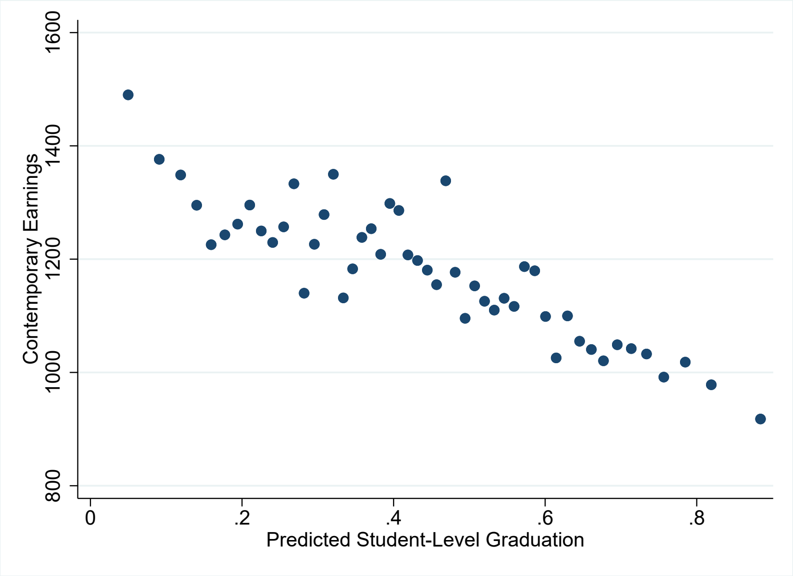


Average Counterfactual Outcomes Per Student

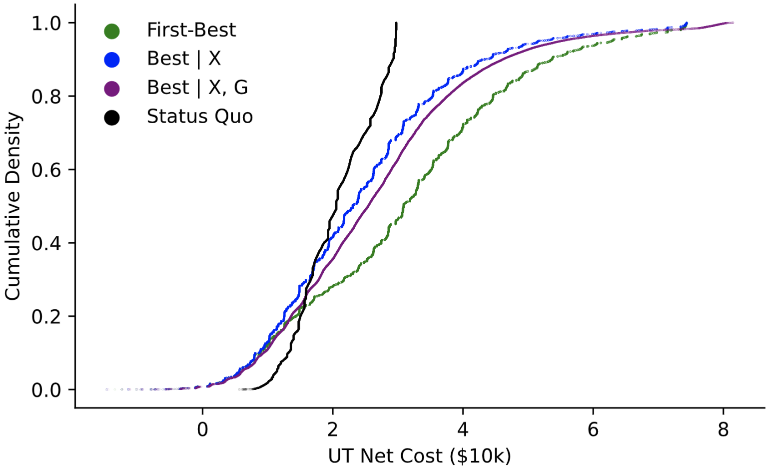
	Social Surplus	Consumer Surplus	Graduation (%)	Enrollment (%)	Revenue	Producer Surplus
(1) First-Best	2.682	2.222	0.550	−1.931	0.318	0.077
(2) Screening	2.145	2.150	−3.524	−0.021	0.090	0.011
(3) Screening + Incentive	2.463	2.101	−3.548	−0.072	0.325	0.013
(4) Status Quo + Incentive	0.679	0.243	1.568	2.522	0.017	0.007

First-Best: Regulator determines personalized aid offers given exact graduation chance

Screening: Regulator sets aid schedule that depends on all observed baseline characteristics

Incentive (loan forgiveness): Aid schedule also depends on ex-post graduation

Cumulative Distributions of Net Cost Across Counterfactual Schedules



Underrepresented Students Benefit Most

Counterfactual aid increases flagship enrollment for the historically underrepresented

- Racial/ethnic minorities
- First-generation
- Fewer Advanced Placement courses
- High schools with low college graduation

Effects for gender and income are mixed across counterfactuals

Conclusion: Why Don't Graduation Incentives Work?

Historically, incentives targeted (constrained) effort, not college choice

- Substantial heterogeneity in students' private info about graduation chances
- Financial aid can increase efficiency and equity through student-university match
- Current need-based aid is too rigid with list prices too low

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Reform: Tie financial aid to graduation for **all** students but **only** at selective universities

- Efficiency: Flexible contracts sort students by private gain
- Equity: Underrepresented students may benefit more from college quality
- Sometimes, higher student welfare $\nrightarrow$ higher graduation

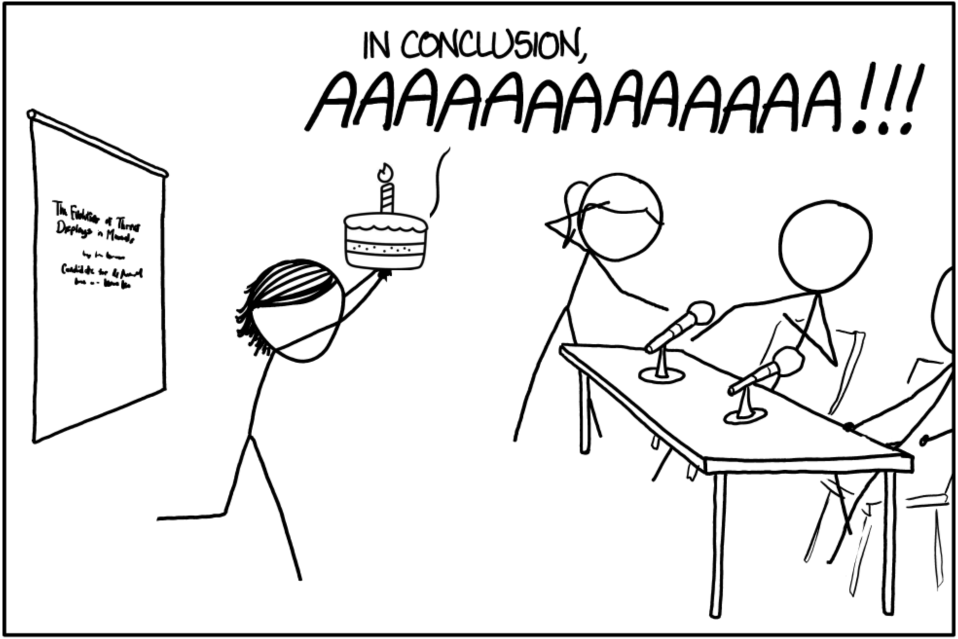
Future Research Combines Chapters

Extend payment contract design to a more complicated setting like US healthcare

- Private insurance → fewer feasible contracts or spillovers across patients
- Group size and structure may moderate altruism
- Service mix, not just quantity
- Robust mechanism design and randomized control trials of “optimal" contracts

Physician payment contracts may complement other policy instruments

- Enrollment caps → location choice and physician-patient match quality
- Insurance risk adjustment → cream-skimming
- Patient cost-sharing → match quality
- Debt relief → better targeting via dynamic heterogeneity



THE BEST THESIS DEFENSE IS A GOOD THESIS OFFENSE.

Contribution

Healthcare disruptions: [Emergency Care] Jena et al., 2017; Gruber, Hoe and Stoye, 2018; Hsia and Shen, 2019; Hoe, 2022; [Short-Term Disruptions in Primary Care] Shurtz et al., 2018; Harris, Liu and McCarthy, 2020; Freedman et al., 2021; Kovacs and Lagarde, 2022;

- Persistent disruption in primary care

Consequences of Physician Retirement: Kwok, 2018; Fadlon and Van Parys, 2020; Bischof and Kaiser, 2021; Simonsen et al., 2021; Zhang, 2022; Sabety, 2023)

- Consequences for nearby patients and test of exclusion

Back

Why Norway?

Automatic reassignment of patients when physicians move or retire

- Random conditional on municipality and availability

Registration system encourages long-term patient-physician relationships

- No confounding variation from patient composition

All physicians face identical financial incentives

Universal public healthcare system: data includes almost all patients + physicians

- Patient registration has far-reaching consequences for health and spending
- Statistical power to estimate small effects, test model predictions

Back

Heterogeneity in the Effect of Enrollment on Hours

	Capacity		Fee Level		Schedule	
	Slack (1)	Binds (2)	Low (3)	High (4)	Part-Time (5)	Full-Time (6)
Enrollment	−0.025	−0.051	−0.045	−0.039	−0.083	−0.005
	(0.023)	(0.027)	(0.027)	(0.030)	(0.004)	(0.010)
	[0.281]	[0.057]	[0.095]	[0.197]	[<0.001]	[0.609]
Dep. Var. Mean	94.515	107.514	84.576	113.236	78.104	113.770
1st Stage F-Stat.	33.577	134.240	83.519	46.769	100.088	66.967
Observations	16,783	18,603	14,677	20,709	12,324	23,062
	Age		Diagnoses		Gender	
	Under 65 (7)	Over 65 (8)	Healthy (9)	Chronic (10)	Male (11)	Female (12)
Enrollment	−0.042	−0.007	−0.037	−0.012	−0.013	−0.036
	(0.020)	(0.006)	(0.020)	(0.006)	(0.007)	(0.019)
	[0.035]	[0.248]	[0.061]	[0.045]	[0.068]	[0.053]
Dep. Var. Mean	72.288	29.061	58.032	43.316	42.905	58.444
1st Stage F-Stat.	112.037	112.037	112.037	112.037	112.037	112.037
Observations	35,386	35,386	35,386	35,386	35,386	35,386

Back

Contribution

Contract Design: **(Theory)** Ellis and McGuire, 1986; Jack, 2005; Choné and Ma, 2011; Naegelen and Mougeot, 2011; Barham and Milliken, 2014; Allard, Jelovac and Léger, 2014; Ji, 2021; Wu, Chen and Li, 2017; Fang and Wu, 2018; Wu, 2020. **(Empirical)** Fortin et al., 2021; Gaynor et al., 2023. **(Insurance Menus)** Azevedo and Gottlieb, 2017; Marone and Sabety, 2022; Ho and Lee, 2023. **(Other Menus)** Bellemare and Shearer, 2013; D'Haultfœuille and Février, 2020; Taburet et al., 2024

- Portable **empirical** framework for menu design with unobserved outcomes

Physician heterogeneity: Epstein and Nicholson, 2009; Hennig-Schmidt, Selten and Wiesen, 2009; Doyle, Ewer and Wagner, 2010; Godager and Wiesen, 2013; Douven, Remmerswaal and Zoutenbier, 2017; Gowrisankaran, Joiner and Léger, 2017; Galizzi et al., 2015; Einav et al., 2021; Chan and Chen, 2022

- **Correlated** cost, altruism, and patient need $\rightarrow$ targeted policy

Physician response to financial incentives: Gaynor, Rebitzer and Taylor, 2004; Clemens and Gottlieb, 2014; Brekke et al., 2017, 2020; Einav, Finkelstein and Mahoney, 2018; Eliason et al., 2018; Song et al., 2019; Xiang, 2021

- Connect treatment response to both spending and **patient health**

Back

Contribution

Price discrimination in higher education: Waldfogel, 2015; Epple et al., 2017, 2019; Epple, Martinez-Mora and Romano, 2021; Fillmore, 2022

- Link to allocative efficiency rather than recover university preferences

Effects of grant aid and graduation incentives: van der Klaauw, 2002; Leuven, Oosterbeek and van der Klaauw, 2010; Gunnes, Kirkebøen and Rønning, 2013; Goldrick-Rab et al., 2016; Hämäläinen, Koerselman and Uusitalo, 2016; Evans and Nguyen, 2019; Denning, Marx and Turner, 2019

- First U.S. estimate of no effect

College Value-Added: Dale and Krueger, 2002, 2014; Mountjoy and Hickman, 2021, Ge et al. 2022, Chetty, et al., 2023

- New reduced-form estimates of heterogeneous returns to flagship university enrollment
- Structural estimates adjusted for asymmetric selection on unobservables

Back

B-On-Time Loans (BOT)

How will students select counterfactual financial aid offers?

- BOT case study: optional zero-interest loans, forgiven with on-time graduation
- Choice reveals private information about graduation chances
- Intended to increase effort: available to all students at all schools

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- 44% graduation rate vs. 20% among other aid recipients
- Controlling for **everything**, BOT "effect" reduces to 12pp over mean of 25%

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Does 12pp reflect the causal effect of incentives or selection on unobserved ability?

- Achievement and need likely don't fully reflect private information
- Estimate causal effect by combining two comparisons (diff-in-RD): discontinuity in unmet need and availability of BOT

Background