

# Voluntary Regulation: Evidence From Medicare Payment Reform

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*of* NORTH CAROLINA  
*at* CHAPEL HILL

# Roadmap

- 1 Introduction
- 2 Experimental Design & Data
- 3 Empirical Findings
- 4 Economic Model
- 5 Estimation & Results
- 6 Counterfactuals

# Presentation Outline

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# Medicare, Fee-For-Service, and Alternative Reimbursement Models

- Medicare was established in 1965 under the SSA and is now administered by CMS.
- Medicare covers individuals who are 65+, qualified disabled, or require dialysis/kidney transplant.
- Medical Part A covers hospital insurance, operates under traditional “fee-for-service” model. Part C (“Medicare Advantage”) operates under capitation.
- As of 2020, nearly 63M enrollees covered by Medicare, with 37.8M enrolled in Medicare Part A accounting for \$380 billion in spending.<sup>1</sup>

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<sup>1</sup>CMS Fast Facts, 2022. Interestingly, overall Medicare enrollment continues to rise (up to 64.5M in 2022), while enrollment in Part A declines (down to 35M in 2022).

# Medicare, Fee-For-Service, and Alternative Reimbursement Models

- Alternative payment models include:
  - Accountable Care Organizations (ACOs),
  - Bundled payments\*,
  - Primary care coordination.
- Alternative payment models account for over 30% of total Medicare spending as of 2016.

# Voluntary Regulation

Market participants willingly decide to opt into voluntary program.

Voluntary regulation not unique to healthcare. Appears in environmental (e.g. pollution), educational (e.g. school vouchers), and energy (e.g. pricing schedules) regulation.

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However, key trade-off exists for regulators:

- Selection on slopes: private information allows participant to forecast gains from changing behavior, net societal benefit.
- Selection on levels: participants opt-in with no behavior change, net societal loss.

Most of the policy debate has been focused on “selection on levels” and has ignored “selection on slopes”. Authors key contribution is in investigating selection on moral hazard by hospitals.

# Preview of Results

- ① Selection on levels quantitatively dominates selection on slopes.
- ② Voluntary regulation already achieves  $\sim \frac{2}{3}$  of the feasible welfare gains in this setting.
- ③ Very difficult to set optimal bundle prices with available information, but small welfare gains are feasible through improved targeting.

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# Comprehensive Care for Joint Replacement Program

- The program, known as CJR, was announced in 2015 and began in April, 2016.
- Covers hip and knee replacement operations; meaningfully large category, accounting for approx. 5% of Medicare stays and spending.
- Under CJR, select hospitals would receive bundled payments (as opposed to FFS).
- Pre-determined, fixed payments are made to the hospital (based on the DRG/modifier), after which the hospital is responsible for all claims on the stay.

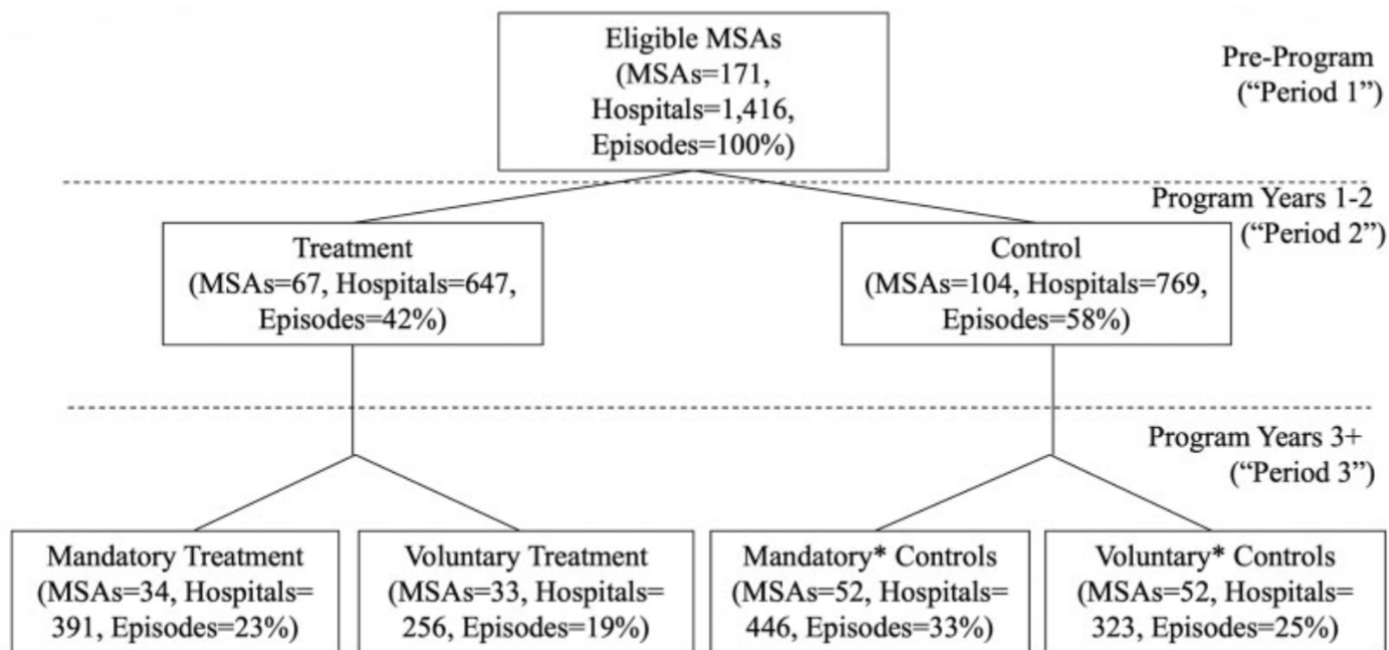
# Comprehensive Care for Joint Replacement Program

- CJR announced as a 5-year randomized controlled trial, with **mandatory** participation for hospitals selected into treatment arm.
- MSAs divided into 8 strata (by past LEJR spending quartile, median population), and randomized to treatment or control.

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- MSAs divided into 8 strata (by past LEJR spending quartile, median population), and randomized to treatment or control.
- Key intervention: in 2017 Senator Tom Price (then head of HHS) successfully led effort to change the program from mandatory to voluntary for **some** of the treatment hospitals.
- Hospitals in 33 of 67 treatment MSAs given one-time opportunity to opt in or out of program, with the decision taking effect in Jan. 2018.
  - Specifically, MSAs with below median-level historical spending on LEJR were given the option to voluntarily participate.

# Comprehensive Care for Joint Replacement Program



# How Do Bundled Payments Actually Work?

## Reconciliation payments:

- Under FFS,  $y_{ht}$  is the average per episode claims submitted to Medicare by hospital  $h$  in year  $t$ .
  - Includes separate claims for the hospital, surgeon, PAC, etc.
- Under CJR,  $b_{ht}$  is the average per episode bundle price at hospital  $h$  in year  $t$ .
- *However*, hospitals in the treatment group continue to submit claims and receive payment from Medicare as they would under FFS.
- Reconciliation occurs at year's end: treatment hospitals receive  $b_{ht} - y_{ht}$  per episode. Gross payment from Medicare is  $b_{ht}$ .



# Two Important Caveats on Hospital Reimbursement

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2. Risk exposure is mitigated for all parties through stop-loss payments:
  - If  $b_{ht} - y_{ht} \leq -\underline{b}$  then hospital pays CMS  $\underline{b}$ .
  - If  $b_{ht} - y_{ht} \geq \bar{b}$ , then Medicare pays hospital  $\bar{b}$ .
  - Stop- loss/gain limits initially set to be small and grow over the course of the program.

# Unintended Changes in Quality?

One concern with the change to bundled payments is the impact on incentives: do hospitals now shirk on quality to save on costs?

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Little evidence to support this concern:

- Prior research finds no change in quality after reimbursement changes to bundled payments (Finkelstein et al. 2018).
- Hospitals only receive reconciliation payments by meeting minimum quality standards (non-binding for vast majority).
- Authors control for quality in average treatment effects, find no effect.

- Medicare enrollment claims from 2013 - 2018:
  - Demographics,
  - Inpatient, outpatient, PAC claims,
  - OOP payments owed,
  - Dates and length-of-stay.
- Hospital ownership type, size (beds), teaching status, and quality measures.
- Bundle prices and reconciliation payments for each hospital (in treatment arm).
  - Impute bundle prices for treatment hospitals that voluntarily select out of program in 2018.
- Final sample includes nearly 380k patients at the 1,416 hospitals (in 171 MSAs) that had at least one LEJR discharge in all three periods.

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# Average Treatment Effects

Following Finkelstein et al. (2018), authors estimate:

$$outcome_{j,2} = \beta_0 + \beta_1 BP_j + \beta_2 outcome_{j,2014} + \beta_3 outcome_{j,2013} + \delta_{s(j)} + \epsilon_j \quad (1)$$

- $outcome_{j,2}$ : average per episode outcome in MSA  $j$ , period 2;
- $BP_j$ : equals 1 if randomly assigned to treatment;
- $\beta_1$ : average treatment effect of bundled payments;
- $outcome_{j,yyyy}$ : lagged outcomes;
- $\delta_{s(j)}$ : strata fixed-effects.

# Average Treatment Effects

TABLE I  
EXPERIMENTAL ESTIMATES DURING THE MANDATORY PARTICIPATION PERIOD

	Control mean	Control std. dev.	Average treatment effect	Standard error	p-value
<i>Panel A: Claims, utilization, and gov't spending (per episode)</i>					
Claims	25,294	3,603	-790	204	.001
Claims for index admission	13,542	2,389	-169	89	.060
Claims for institutional PAC	4,119	1,378	-499	128	.001
Claims for home health	1,800	918	-89	59	.131
Other claims	5,832	532	28	55	.610
Utilization					
Number of days in index admission	2.6	0.4	-0.1	0.0	.217
Number of days in institutional PAC	7.7	2.3	-0.6	0.2	.014
Discharge destination					
Institutional PAC	0.313	0.104	-0.034	0.009	.001
Home health agency	0.339	0.196	0.004	0.018	.812
Home (w/o home health agency)	0.329	0.232	0.042	0.018	.020
Other	0.019	0.032	-0.004	0.002	.052
Government spending	25,294	3,603	40	208	.848
<i>Panel B: Quality measures</i>					
Complication rate	0.011	0.005	0.001	0.001	.255
ER visit during episode	0.198	0.027	0.003	0.003	.399
90-day all cause readmission rate	0.102	0.015	-0.001	0.002	.725
<i>Panel C: Admissions and patient composition</i>					
LEJR admissions (per 1,000 enrollees)	29.9	15.8	-0.8	0.5	.095
CJR-eligible LEJR admissions (per 1,000 enrollees)	23.6	11.3	0.1	0.5	.889
Elixhauser comorbidity score	2.4	0.3	0.0	0.0	1.00



# Key Findings From Average Treatment Effects Estimation

- ① Significant decline in both total & PAC claims\*,
- ② Decline in discharge to PAC accompanied by increase to home without health agency (likely cascading effect)\*,
- ③ No change in overall Medicare spending,
- ④ No detectable change in measurable quality,
- ⑤ No “cream skimming” effect,
- ⑥ Dynamic effects are not first order: treatment effects are immediate and steady over time, indicating little learning by doing.
  - Treatment effects do not fade out for voluntary hospitals prior to 2018, indicating no anticipatory effect.

► Effects Over Time

# Heterogeneity in Levels and Slopes

Substantial heterogeneity across hospitals masked by prior MSA level analysis. Same regression run at hospital level yields:

$$outcome_{h,2} = \beta_0 + \beta_{1,h}BP_h + \beta_2 outcome_{h,2014} + \beta_3 outcome_{h,2013} + \delta_{s(h)} + \epsilon_h \quad (2)$$

TABLE II  
CORRELATES OF LEVELS AND SLOPES

	Panel A: Heterogeneity in levels						Panel B: Heterogeneity in slopes					
	Claims		Claims for institutional PAC		Probability of discharge to PAC		Claims		Claims for institutional PAC		Probability of discharge to PAC	
Mean (std. dev.)	28,357	(5,998)	5,814	(3,021)	0.455	(0.187)	-1,154	(3,054)	-1,011	(1,809)	-0.057	(0.105)
Coefficient (std. err.) from bivariate regression												
Number of CJR episodes	-5.31	(1.56)	-3.39	(0.69)	-0.0001	(0.0001)	-0.85	(0.57)	-1.10	(0.37)	-0.00003	(0.00002)
Quality	-441	(41)	-197	(18)	-0.010	(0.001)	-123	(24)	-77	(15)	-0.004	(0.001)
Number of beds	3.90	(1.21)	0.62	(0.32)	0.0001	(0.00003)	0.53	(0.46)	0.09	(0.20)	0.000004	(0.00001)
Teaching	4,528	(599)	561	(258)	0.049	(0.021)	819	(525)	-212	(241)	-0.025	(0.017)
For-profit	-3,030	(660)	-387	(304)	-0.064	(0.025)	-1,012	(651)	-414	(292)	-0.030	(0.020)
Nonprofit	-219	(596)	369	(264)	0.008	(0.023)	-32	(617)	-160	(246)	-0.012	(0.018)

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# Observable Hospital Characteristics Do Not Explain Variation

- Exercise of variance decomposition (across levels and slopes) shows that observed hospital characteristics explain little cross-variation.

► Decomposition

- Interviews from prior studies show that hospitals highly value “physician champions” who lead the hospital’s behavioral response (slope) to bundled payments (Lewin Group, 2019b).

# Voluntary Selection

Clear evidence for selection on levels. Less so for selection on slopes.

TABLE III  
SELECTION

	Voluntary control (1)	Voluntary select-in (2)	Voluntary select-out (3)	<i>p</i> -value of select-in vs. select-out difference (4)
Number of hospitals	323	73	183	
Number of episodes in period 1	51,469	14,664	24,777	
Percent of episodes in period 1		37.2%	62.8%	
<i>Panel A: Selection on levels (period 1 outcomes per episode)</i>				
Claims	26,524 (5,367)	26,146 (4,176)	27,776 (5,497)	.03
Claims for institutional PAC	4,811 (2,402)	4,681 (2,054)	5,551 (2,446)	.01
Share discharged to institutional PAC	36.9% (16.0%)	37.3% (16.2%)	41.6% (14.5%)	.10
<i>Panel B: Selection on slopes</i>				
Impact on episode claims		-791 (1,931)	-665 (2,826)	.73
Impact on institutional PAC claims		-518 (973)	-176 (1,474)	.05
Impact on share discharged to institutional PAC		-3.3% (7.8%)	-1.2% (9.2%)	.12
<i>Panel C: Selection on hospital characteristics</i>				
Mean number of CJR episodes	306	320	252	.13
Mean number of beds	339	320	362	.43
Teaching	18.7%	4.3%	16.1%	.02
For-profit	17.5%	26.6%	12.5%	.06
Nonprofit	78.5%	63.4%	68.6%	.56
Government-owned	4.0%	10.0%	18.9%	.20
Mean quality score	11.7	13.1	10.6	.001

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- FFS claims at hospital  $h$  denoted by  $\lambda_h$ , where  $\lambda_h = f_h^{HOSP} + f_h^{OTH}$ .
- Bundled payments average reimbursement per episode denoted by  $b_h$ .
- Costs denoted  $c_h^j$  for  $j \in \{HOSP, OTH\}$ , with the assumption  $c_h^{OTH} = f_h^{OTH}$  (for tractability...).
- $f_h^{HOSP}$  are fixed by DRG under the PPS.

# Bundled Payments Maximization Problem

Under FFS, hospitals simply receive profits  $\pi_h^{FFS} = f_h^{HOSP} - c_h^{HOSP}$ .

However, hospitals under bundled payments also incur costs from downstream providers' claims, thus their problem becomes:

$$\pi_h^{BP} = \max_e (b_h - [(c_h^{HOSP} + f_h^{OTH}) - e] - \phi_h(e)), \quad (3)$$

where  $\phi_h(e)$  represents the cost to the hospital of exerting effort to reduce downstream costs by  $e$ . Note, we can just think of  $f_h^{OTH}$  as  $c_h^{OTH}$ .

Effort cost has standard properties:  $\phi_h(0) = 0$ ,  $\phi_h' > 0$ , and  $\phi_h'' > 0$ .



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**FOC yields optimal (and first-best) effort  $\phi_h'(e_h^*) = 1$ .**

# Participation Incentive

Authors assume quadratic effort costs,  $\phi_h(e) = \frac{e^2}{2\omega_h}$ , where  $\omega_h$  is a hospital-specific parameter to be estimated.

$$\phi'_h(e_h^*) = 1 \implies e_h^* = \omega_h \implies \phi_h(e_h^*) = \frac{\omega_h}{2} \implies \pi_h^{BP} = b_h - (c_h^{HOSP} + f_h^{OTH} - \omega_h).$$

Hospitals (with the option) will only select into bundled payments if  $\pi_h^{BP} > \pi_h^{FFS}$ :

$$BP_h = 1 \iff (b_h - \lambda_h) + \frac{\omega_h}{2} > 0. \quad (4)$$

Interpretation?

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Interpretation:

- Level effect:  $(b_h - \lambda_h)$
- Slope effect:  $\frac{\omega_h}{2}$

$$W = S + \pi - (1 - \Lambda)G, \quad (5)$$

- $W$ : social welfare;
- $S$ : consumer surplus (assumed fixed, supported by prior evidence);
- $\pi$ : hospital profits;
- $G$ : government (Medicare) spending;
- $\Lambda$ : marginal cost of public funds ( $> 0$ ).
  - Captures DWL associated with distortionary taxation.

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  - Captures DWL associated with distortionary taxation. Assumed to be 0.15!

# Socially Optimal Participation

Akin to the hospital's problem, participation is socially optimal when:

$$W_{BP} > W_{FFS} \iff -\Lambda(b_h - \lambda_h) + \frac{\omega_h}{2} > 0. \quad (6)$$

Difference from prior optimality condition?

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Difference from prior optimality condition?  $\Lambda(b_h - \lambda_h)$  captures the social cost of public funds transferred to hospitals based on selection on levels.

Rephrased, participation is only welfare enhancing when the slope effect is greater than the cost-weighted level effect.

# Socially Optimal Participation

Only socially optimal when  $\frac{\omega_h}{2} > \Lambda(b_h - \lambda_h)$ .

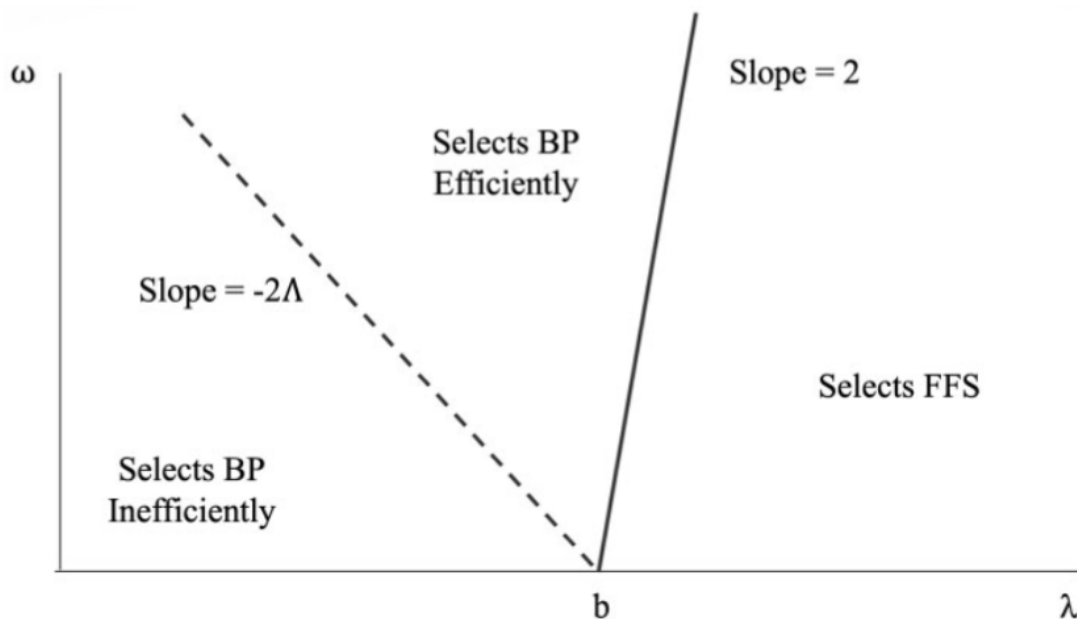


FIGURE II

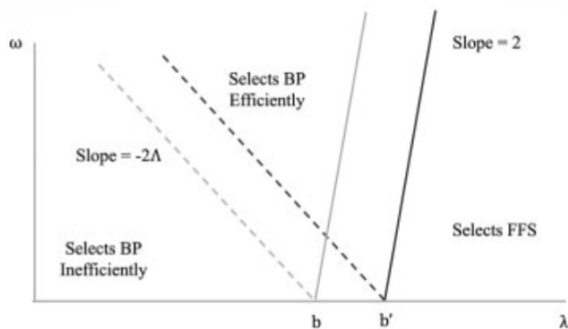
Hospital Selection Into Bundled Payment and Social Welfare Implications



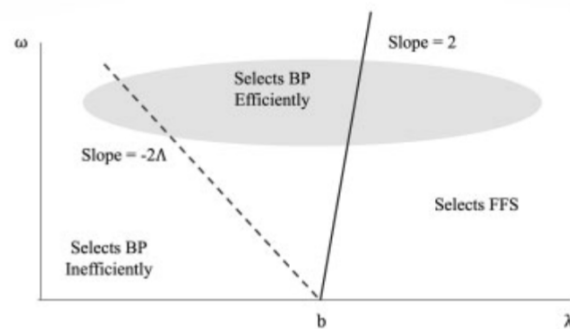
# Targeting

Precise targeting (i.e. small  $b_h - \lambda_h$ )  $\implies$  Panel (D), the desired outcome, is achievable.

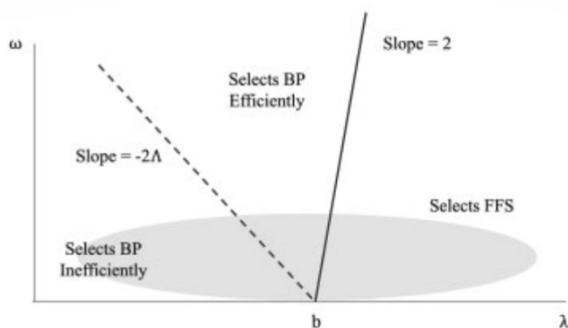
(A) Impact of Raising Bundle Prices



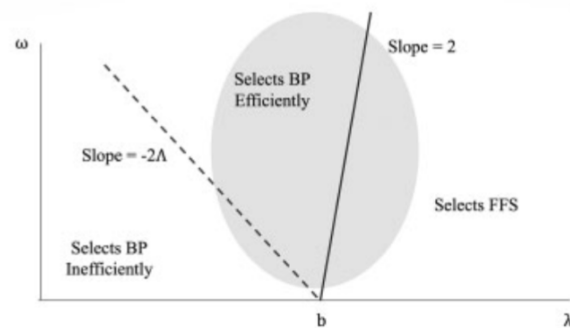
(B) Larger  $\omega$ , More Variable  $\lambda$



(C) Smaller  $\omega$ , More Variable  $\lambda$



(D) More Variable  $\omega$ , Less Variable  $\lambda$



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# Econometric Specification

Hospital  $h$  associated with pair  $\{\lambda_h, \omega_h\}$ . Authors fix  $\omega_h$ , but allow  $\lambda_h$  to evolve over time following:

$$\ln \lambda_{h,t} = \ln \lambda_h + \gamma_t + \epsilon_{h,t}. \quad (7)$$

- $t = 1, 2, 3$ ;
- $\gamma_t$ : period-specific indicators, normalized  $\gamma_2 = 0$ ;
- $\epsilon_{h,t}$ : i.i.d.  $\sim N(0, \sigma_\epsilon^2)$ .

Lastly,  $\{\lambda_h, \omega_h\}$  are assumed to be jointly log-normally distributed:

$$\begin{pmatrix} \ln \lambda_h \\ \ln \omega_h \end{pmatrix} \sim N \left( \begin{pmatrix} x_h' \beta^\lambda \\ x_h' \beta^\omega \end{pmatrix}, \begin{pmatrix} \sigma_\lambda^2 & \rho \sigma_\lambda \sigma_\omega \\ \rho \sigma_\lambda \sigma_\omega & \sigma_\omega^2 \end{pmatrix} \right)$$

- $x_h$ : hospital characteristics and strata fixed effects;
- $\rho$ : correlation parameter.

Authors observe claims  $\{y_{h,t}\}_{t=1,2,3}$  and participation  $\{BP_{h,t}\}_{t=1,2,3}$ , meaning submitted claims are characterized by:

$$y_{h,t} = \lambda_{h,t} - BP_{h,t}\omega_h. \quad (8)$$

Voluntary participation decision in  $t=3$  becomes:

$$BP_{h,3} = 1 \iff (b_{h,3} - \lambda_{h,t}) + \frac{\omega_h}{2} > 0,$$

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- $\nu_h$ : nebulous hospital “choice shifter”, i.i.d.  $\sim N(x'_h\beta^\nu, \sigma_\nu^2)$ .

# Identification I

- “Level” parameters:  $\beta^\lambda, \sigma_\lambda, \gamma_1, \gamma_3, \sigma_\epsilon$ 
  - Identified using  $\{\lambda_{h,t}\}_{t=1,2,3}$  and a standard random effects model on control group hospitals.
  - Given the setting is a RCT, the control group parameters will be valid across all hospitals.
- “Slope” parameters:  $\beta^\omega, \sigma_\omega$ 
  - Using  $\gamma_1$  from above, average difference between  $\lambda_{h,1}$  and  $\lambda_{h,2} - \omega_h$  (i.e. observed claims for treatment group) after netting out  $\gamma_1$  identifies  $\beta_\omega$ .
  - Residual dispersion in treatment outcomes after controlling for the evolution of  $\lambda_{h,t}$  identifies  $\sigma_\omega$ .

# Identification II

- $\rho$  identified similarly to  $\sigma_\omega$ :
  - Correlating the observed change in claims between  $t=1$  and  $t=2$  for treatment group with  $t=1$  claims, and adjusting for noise ( $\sigma_\epsilon$ ), identifies the correlation parameter.
- Choice shifters:  $\beta^\nu, \sigma_\nu$ 
  - Previously identified joint distribution of  $\{\lambda_h, \omega_h\}$  allows for predictions of the model (i.e.  $\widehat{BP_{h,3}}$ ).
  - Any systematic deviations from the model predictions and observed realizations identify  $(\beta^\nu, \sigma_\nu)$ .



- $\rho$  identified similarly to  $\sigma_\omega$ :
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- Choice shifters:  $\beta^\nu, \sigma_\nu$ 
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  - Any systematic deviations from the model predictions and observed realizations identify  $(\beta^\nu, \sigma_\nu)$ .
  - Thoughts on the  $\nu$  “choice shifter”?

Optimization (MLE) infeasible here due to large number of parameters and numerical integration in the participation equation. Thus, authors employ a Markov Chain Monte Carlo (MCMC) Gibbs Sampler.

- Model is already fully parametrized, and Gibbs sampler allows authors to parametrize latent variables  $\lambda_h$ ,  $\omega_h$ , and  $\nu_h$ .
- Main idea:
  - Use the priors to derive *conditional* posterior distributions on all other parameters and observable data, then draw each parameter one at a time.
  - Repeat the process iteratively 100k times, discard first 10k iterations (to allow for convergence stable posterior distribution), and use simulations to produce the posterior means and standard deviations.
- Full details of the sampler are outside the scope of this presentation (see Online Appendix C if interested).

# Posterior Estimation Results

TABLE IV  
PARAMETER ESTIMATES

	ln( $\lambda$ ) equation		ln( $\omega$ ) equation		$\nu$ equation	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
<i>Panel A: Equation-specific parameters</i>						
Constant*	10.165	0.005	4.895	0.293	-7,984	12,616
ln(CJR Episodes)	-0.066	0.004	-0.559	0.145	4,930	7,601
ln(Beds)	0.050	0.006	0.502	0.247	1,172	5,065
Quality score	-0.169	0.022	4.895	1.217	43,473	54,507
Teaching	0.017	0.002	-0.034	0.084	-2,275	3,939
For-profit	-0.008	0.002	0.078	0.066	3,912	4,517
Government-owned	-0.002	0.001	-0.102	0.060	-621	1,322
Nonprofit	omitted category		omitted category		omitted category	
Strata fixed effects	yes		yes		yes	
$\sigma$	0.139	0.003	0.727	0.117	24,669	27,548
<i>Panel B: Additional model parameters</i>						
$\gamma_1$	0.067	0.004				
$\gamma_2$	normalized to 0					
$\gamma_3$	0.015	0.003				
$\sigma_\epsilon$	0.073	0.001				
$\rho$	0.143	0.196				

- Episode-weighted mean (across strata) of model parameters.
- Large hospitals assoc. with higher levels/slopes; opposite for high volume hospitals, etc.
- U-shaped time trend ( $\gamma$ 's).

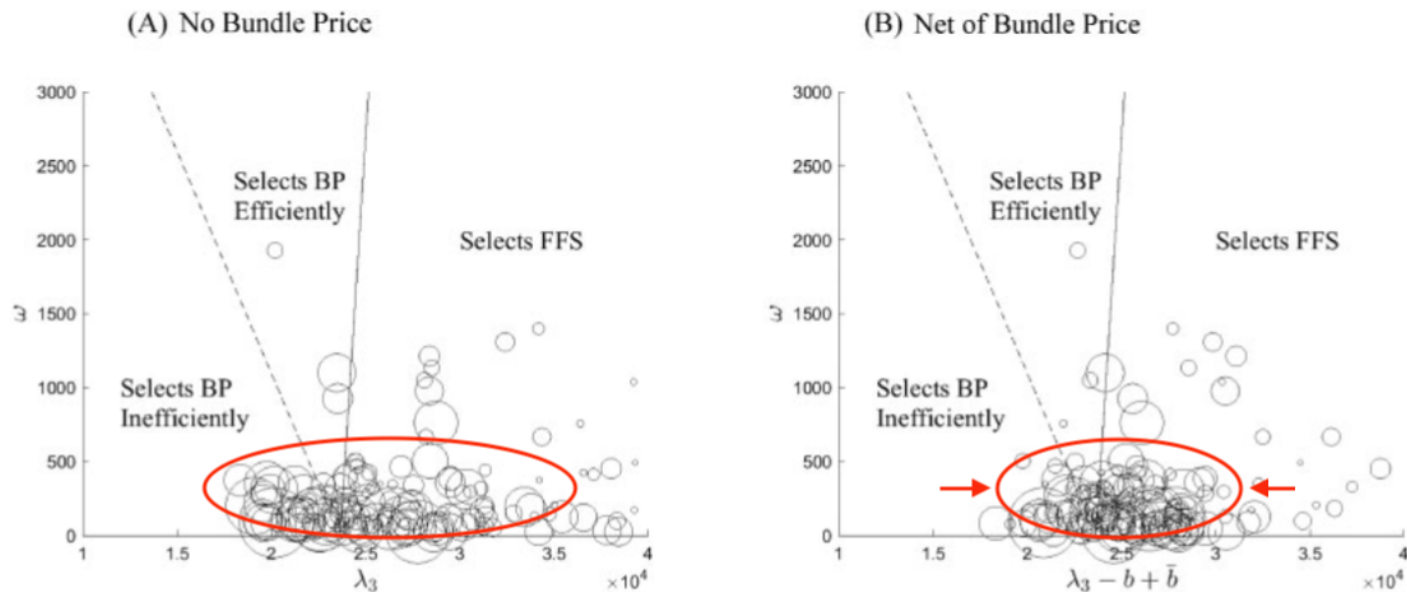
# Posterior Estimation Results

TABLE V  
POSTERIOR DISTRIBUTIONS

	E(x)	SD(x)	P5	P25	P50	P75	P95
<i>Panel A: All hospitals</i>							
$\ln(\lambda_h)$	10.17	0.19	9.89	10.04	10.14	10.27	10.51
$\ln(\omega_h)$	4.895	1.747	1.835	3.717	5.020	6.179	7.528
$\lambda_{h3}$	27,028	5,960	19,621	23,043	25,921	29,786	38,238
$\omega_h$	485	1,180	7	44	160	500	1,902
<i>Panel B: Hospitals in the voluntary treatment group only</i>							
$\lambda_h$	25,247	4,527	19,532	22,207	24,390	27,370	33,723
$\lambda_{h3}$	25,517	5,109	19,333	21,949	24,597	27,841	35,277
$b_h$	23,659	3,744	19,530	21,174	22,785	25,110	31,141
$b_h - \lambda_h e^{\gamma_3}$	-1,961	2,640	-6,728	-3,224	-1,706	-358	1,390
$\omega_h$	246	611	5	24	73	218	1,014
$(b_h - \lambda_h e^{\gamma_3}) + \frac{\omega_h}{2}$	-1,838	2,623	-6,593	-3,074	-1,584	-258	1,477
$\nu_h$	-7,719	31,103	-59,838	-28,472	-7,227	13,454	42,939

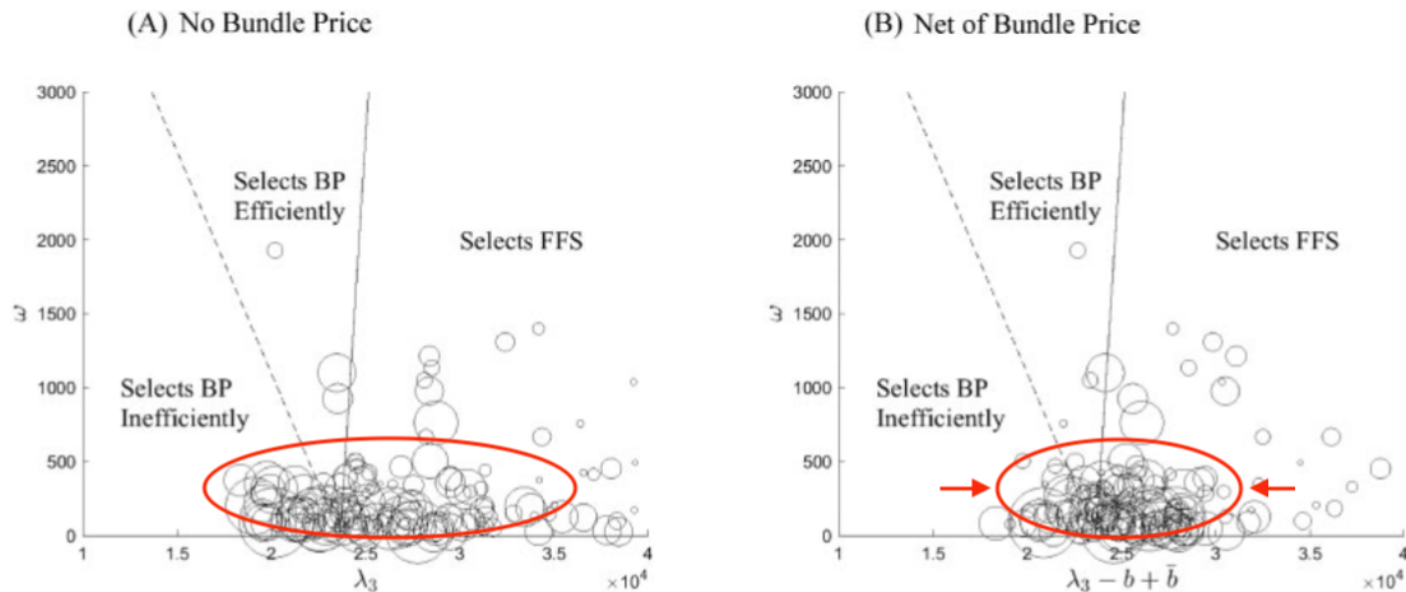
- Lower level of mean claims at voluntary treatment hospitals.
- Smaller  $\omega_h$ , more variable  $\lambda_h$ .
- Observables account for  $< \frac{1}{3}$  of cross-hosp. variation in levels.

# Heterogeneous Selection by Voluntary Treatment Hospitals



Netting out bundle price reduces some of the dispersion, but not enough to eliminate all socially undesirable selection.

# Heterogeneous Selection by Voluntary Treatment Hospitals



Netting out bundle price reduces some of the dispersion, but not enough to eliminate all socially undesirable selection. Again, thoughts on  $\Lambda$ ?

# Presentation Outline

- 1 Introduction
- 2 Experimental Design & Data
- 3 Empirical Findings
- 4 Economic Model
- 5 Estimation & Results
- 6 Counterfactuals

# Overview of Counterfactuals

Focus on two counterfactuals:

- 1 Social welfare under FFS, mandatory bundled payments, and voluntary bundled payments.
- 2 Social welfare under alternative bundle prices within the voluntary regime.

Analyses will only consider the 256 hospitals in the voluntary treatment group, so that there is no reliance on imputed bundle prices.



# Does Bundled Payments Actually Increase Welfare?

TABLE VI  
COUNTERFACTUALS

	Ignoring choice shifter				
	Percent selecting in (1)	Government spending (2)	Relative social costs (3)	Relative hospital profit (4)	Relative social surplus (5)
<i>Panel A: Mandatory vs. voluntary</i>					
Mandatory FFS (benchmark)	0.0	25,517	0	0	0
Mandatory bundled payment	100.0	23,659	−2,137	−1,736	402
Voluntary bundled payment	38.8	25,055	−532	−405	127
<i>Panel B: Alternative voluntary regimes with different bundle prices</i>					
Perfect targeting	38.7	24,870	−745	−589	155
Feasible targeting	38.5	24,908	−700	−551	150
Observed targeting	38.7	25,018	−574	−440	133
No targeting	39.1	25,302	−248	−157	91
Narrow bundle, no targeting	38.5	25,045	−543	−413	130

- $(3) = \Delta G * (1 + \Lambda) = (b_h - \lambda_h) * (1 + \Lambda),$
- $(4) = (b_h - \lambda_h) + \frac{\omega_h}{2},$
- $(5) = (4) - (3) = (b_h - \lambda_h) + \frac{\omega_h}{2} - (b_h - \lambda_h) * (1 + \Lambda) = -\Lambda(b_h - \lambda_h) + \frac{\omega_h}{2},$
- When choice shifter  $\nu_h$  is ignored, **effects are economically small.**

# Can Alternative Pricing Increase Gains Under Voluntary Participation?

TABLE VI  
COUNTERFACTUALS

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- Approximate observed bundle prices assuming  $\{b_{h,3}, \lambda_{h,3}\}$  are joint log-normally distributed.
- Feasible targeting increases average welfare by \$17 per episode (“feasible” meaning  $\ln b_h$  perfectly correlated with  $\ln \lambda_h$  (see equation (7))).
- No targeting sets uniform bundle prices.
- Observed targeting already generates  $\sim \frac{2}{3}$  of the feasible welfare gains.

# Appendix

TABLE A.3  
Experimental Estimates: Effects Over Time

	Period	Control Mean	SD	Change with Bundled Payment	SE	P-Value
<b>Panel A: All MSAs</b>						
Total Episode Claims	2016 Q2	25,337	3,642	-591	232	0.02
	2016 Q3/Q4	25,552	3,710	-739	223	0.01
	2017 Q1/Q2	24,996	3,624	-684	224	0.01
	2017 Q3/Q4	25,427	3,744	-900	253	0.01
Claims for Institutional PAC	2016 Q2	4,296	1,499	-443	156	0.01
	2016 Q3/Q4	4,246	1,445	-406	140	0.01
	2017 Q1/Q2	3,905	1,390	-502	139	0.01
	2017 Q3/Q4	4,070	1,601	-635	161	0.01
Share Discharged to Institutional PAC	2016 Q2	0.34	0.12	-0.040	0.010	0.01
	2016 Q3/Q4	0.32	0.11	-0.027	0.009	0.01
	2017 Q1/Q2	0.30	0.10	-0.034	0.009	0.01
	2017 Q3/Q4	0.29	0.10	-0.031	0.009	0.01
<b>Panel B: Voluntary MSAs</b>						
Total Episode Claims	2016 Q2	25,222	4,455	-573	353	0.11
	2016 Q3/Q4	25,335	4,575	-629	344	0.08
	2017 Q1/Q2	24,993	4,376	-719	335	0.04
	2017 Q3/Q4	25,305	4,614	-1,001	362	0.01
Claims for Institutional PAC	2016 Q2	3,883	1,537	-328	209	0.13
	2016 Q3/Q4	3,763	1,489	-255	190	0.19
	2017 Q1/Q2	3,557	1,393	-448	174	0.02
	2017 Q3/Q4	3,585	1,708	-442	213	0.05
Share Discharged to Institutional PAC	2016 Q2	0.29	0.10	-0.020	0.014	0.16
	2016 Q3/Q4	0.27	0.08	-0.013	0.012	0.28
	2017 Q1/Q2	0.25	0.08	-0.024	0.011	0.04
	2017 Q3/Q4	0.24	0.08	-0.017	0.011	0.13
<b>Panel C: Mandatory MSAs</b>						
Total Episode Claims	2016 Q2	25,452	2,631	-483	347	0.17
	2016 Q3/Q4	25,770	2,601	-671	313	0.04
	2017 Q1/Q2	24,998	2,715	-616	327	0.07
	2017 Q3/Q4	25,549	2,644	-713	391	0.08
	2018 Q1/Q2	25,857	2,589	-959	406	0.03
	2018 Q3	26,214	2,783	-1,282	396	0.01
Claims for Institutional PAC	2016 Q2	4,709	1,352	-486	236	0.05
	2016 Q3/Q4	4,730	1,235	-435	208	0.05
	2017 Q1/Q2	4,254	1,310	-481	219	0.04
	2017 Q3/Q4	4,555	1,334	-752	244	0.01
	2018 Q1/Q2	4,591	1,165	-644	254	0.02
	2018 Q3	4,907	1,418	-901	279	0.01
Share Discharged to Institutional PAC	2016 Q2	0.40	0.11	-0.053	0.016	0.01
	2016 Q3/Q4	0.37	0.11	-0.033	0.014	0.03
	2017 Q1/Q2	0.34	0.10	-0.039	0.014	0.01
	2017 Q3/Q4	0.34	0.09	-0.048	0.014	0.01
	2018 Q1/Q2	0.35	0.07	-0.059	0.014	0.01
	2018 Q3	0.35	0.09	-0.054	0.017	0.01

**TABLE A.5**  
**Correlates of Cross-Hospital Heterogeneity**

	<b>Panel A: Heterogeneity in Levels</b>			<b>Panel B: Heterogeneity in Slopes</b>		
	Total Episode Claims	Institutional PAC Claims	Probability of Discharge to PAC	Total Episode Claims	Institutional PAC Claims	Probability of Discharge to PAC
Unconditional S.D. of Hospital Fixed Effects	5,998	3,021	0.187	3,054	1,809	0.105
S.D. of Hospital Fixed Effects with additional controls:						
Number of CJR Episodes	5,843 (97.4%)	2,894 (95.8%)	0.183 (98.1%)	3,055 (100.0%)	1,799 (99.4%)	0.105 (99.9%)
Quality	5,604 (93.4%)	2,867 (94.9%)	0.180 (96.2%)	3,026 (99.1%)	1,778 (98.3%)	0.103 (98.0%)
Number of Beds	5,864 (97.8%)	3,017 (99.9%)	0.186 (99.7%)	3,048 (99.8%)	1,804 (99.7%)	0.104 (99.7%)
Teaching	5,751 (95.9%)	3,017 (99.9%)	0.186 (99.6%)	3,041 (99.6%)	1,802 (99.6%)	0.104 (99.4%)
Ownership (For-Profit, Non-Profit, Government)	5,896 (98.3%)	3,006 (99.5%)	0.185 (98.9%)	3,041 (99.6%)	1,809 (100.0%)	0.105 (99.9%)
Strata Fixed Effects	5,718 (95.3%)	2,882 (95.4%)	0.173 (92.8%)	3,054 (100.0%)	1,809 (100.0%)	0.105 (100.0%)
MSA Fixed Effects	4,532 (75.6%)	2,557 (84.6%)	0.139 (74.5%)	2,665 (87.2%)	1,685 (93.2%)	0.092 (87.9%)
All of the above	3,537 (59.0%)	2,236 (74.0%)	0.125 (66.8%)	2,637 (86.4%)	1,638 (90.5%)	0.090 (85.9%)
All of the above, as well as all observed patient characteristics	2,830 (47.2%)	1,687 (55.8%)	0.107 (57.4%)	2,169 (71.0%)	1,236 (68.3%)	0.077 (73.1%)

◀ Return

# Choice Shifter Costs Considered “Real” (Welfare-Relevant)

TABLE A.10  
Counterfactuals Incorporating Choice Shifter

	Share Selecting In	Government Spending	Relative Social Costs	<u>Incorporating Choice Shifter</u>	
	(1)	(2)	(3)	Relative Hospital Profit (4)	Relative Social Surplus (5)
<b>Panel A: Mandatory vs. Voluntary</b>					
Mandatory FFS (Benchmark)	0.0%	25,517	0	0	0
Mandatory Bundled Payment	100.0%	23,659	-2,137	-9,455	-7,318
Voluntary Bundled Payment	38.8%	25,055	-532	8,393	8,925
<b>Panel B: Alternative Voluntary Regimes with Different Bundle Prices</b>					
Perfect targeting	38.7%	24,870	-745	8,225	8,970
Feasible targeting	38.5%	24,908	-700	8,232	8,932
Observed targeting	38.7%	25,018	-574	8,302	8,876
No targeting	39.1%	25,302	-248	8,526	8,773
Narrow bundle, no targeting	38.5%	25,045	-543	8,330	8,873

Sorting on  $\nu_h$  leads to large welfare surplus under the voluntary regime, in part due to large dispersion in  $\nu_h$  across hospitals.

[Return](#)