Wait Times for Surgery in the U.S.: Measurement and Allocative Efficiency in Private Insurance

TSE Health Economics Conference

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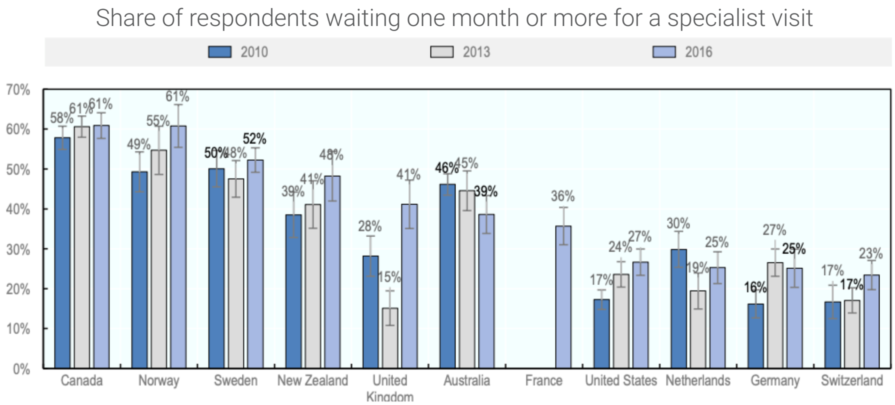
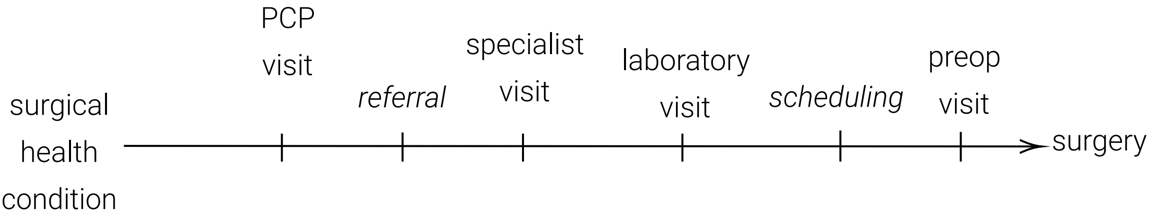
Motivation: Wait Times in Surgical Care Delivery

- Queues for primary/specialty/surgical care common in many healthcare systems



Source: (OECD, 2020). OECD calculations based on 2013 and 2016 Commonwealth Fund Health Policy Surveys. 95% confidence intervals shown by H.

Motivation: Wait Times in Surgical Care Delivery



- Path to surgery combines services: generalist + specialist + imaging/labs + surgeon

Motivation: Wait Times in Surgical Care Delivery

Why is this measurement/analysis difficult?

- Outside of centralized systems (NHS, US V.A.), rare to record wait times (Viberg et al., 2013)
- Survey samples are too small to permit heterogeneity analysis or research designs
- Wait measures often capture only a fraction of care trajectory (e.g. pre-op to surgery)

Research Goals/Approach

1. Characterize how long patients wait for surgical care in the US
   - → Propose a framework to measure wait times using insurance claims
   - → Apply framework to care trajectories for multiple common surgical procedures
2. Identify the causal effect of waiting on patient outcomes and spending
   - → Use an instrumental variables approach based on network congestion
   - → Estimate heterogeneity in treatment effects by patient characteristics
3. Given heterogeneity in wait adverse effects, alternative allocations of surgical capacity

Contributions to the Literature

1. Theory and empirics of waiting time for health care: Lindsay and Feigenbaum, 1984; Cullis, Jones, and Propper, 2000; Gravelle and Siciliani, 2008; Agarwal et al., 2019; Sweat, 2023; Chan and Gruber, 2020; Mark, 2020; Russo, 2023; Huitfeldt, Marone, and Waldinger, 2024
   → Empirics with focus on surgical wait times in U.S. employer-sponsored insurance
2. Health effects of waiting time: Sobolev et al., 2006; Sobolev and Fradet, 2008; Hodge et al., 2007; Nikolova, Harrison, and Sutton, 2016; Moscelli, Siciliani, and Tonei, 2016; Costantini, 2025; Godøy et al., 2024
   → New measure, multiple surgeries, post-surgical medical outcomes, congestion design
3. Economic objects from high-dimensional health care data: **Risk** Einav et al., 2018; **Quality/Skill** Mullainathan and Obermeyer, 2022;Chan, Gentzkow, and Yu, 2022;Olenski and Sacher, 2024; **Diagnostic Support** Agarwal et al., 2023
   → Measure when surgery need becomes detectable in health insurance claims

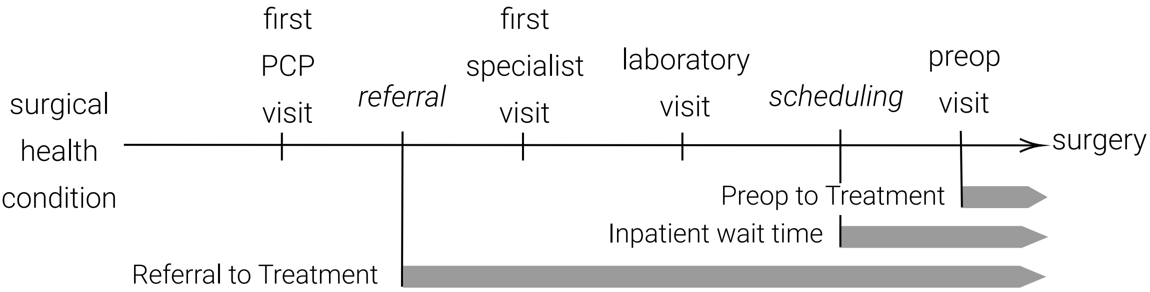
Roadmap

Detection to Treatment: Measuring Wait Times to Surgery

Heterogeneity in Wait Times for Surgery in U.S Private Insurance

Wait Times and Adverse Health Outcomes

Surgical Trajectories and Existing Wait Times Definitions



- Typical alternative measures differ in fraction of care trajectory they capture
- Administrative markers *referral, scheduling* not always recorded
- Specialist visits in the US often occur without referrals (Forrest and Reid, 1997)

Stylized Surgical Wait Time Model and Measurement in Claims

Underlying objects in the scheduling of a given surgery k:

- Patient i with fixed severity σ_i and surgery need r_{ikt} evolves over visits t
- Surgery recommended at $d^*_{ik} = \min\{t : r_{ikt} \geq \gamma_k(\sigma_i)\}$ and performed at $T_{ik} \geq d^*_{ik}$

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Challenge: r_{ikt}, $\gamma_k(\cdot)$, d^*_{ik} unobserved; we observe T_{ik} and claims up to t: $\mathcal{H}_{it} = \{x_{i\tau}\}_{\tau \leq t}$

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$\Rightarrow$ Estimate probability of surgery given trajectory $\widehat{p}_{ikt} = \widehat{\mathbb{P}}(i \text{ receives surgery } k \mid \mathcal{H}_{it})$

- Implied estimated "decision": detection date $\widehat{d}_{ik} = \min\{t : \widehat{p}_{ikt} \geq \bar{p}\}$
- **Detection to treatment** as $\widehat{w}_{ik} = T_{ik} - \widehat{d}_{ik}$

From Measurement to Health Outcomes

Estimand of interest for policy is causal effect α of additional wait on health outcomes:

$$y_i = \alpha w_i^* + \boldsymbol{x}_i' \boldsymbol{\beta} + u_i$$

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Estimation challenges stem from endogeneity of wait times and their measurement

- Selection: severity σ_i enters doctors' scheduling and outcomes $\implies \operatorname{Cov}(w_i^*, u_i) \neq 0$
- Measurement error as we observe $\widehat{w}_i = w_i^* + \eta_i$

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Exploit exogenous congestion in a patient's network during surgical care pathway

- Construct instrument z_i shifting w_i^* such that $\mathrm{Cov}(z_i, u_i) = 0$ and $\mathrm{Cov}(z_i, \eta_i) = 0$

Data, Sample Selection, and Implementation

(1) Data: sample from *Marketscan*'s employer-sponsored health insurance claims

– Limited demographics: age, gender, plan characteristics

+ Sample size: thousands of surgical patients for many different surgeries

+ Longitudinal: can select patients observed $2+$ years pre surgery and $1+$ year after

(2) Surgical sample: 14 surgeries selected from most common US procedures

- Approx. 1 million patients in years $2007 - 2013$
- Cataract, cholecystectomy, coronary bypass, joint replacements, transplants, etc...

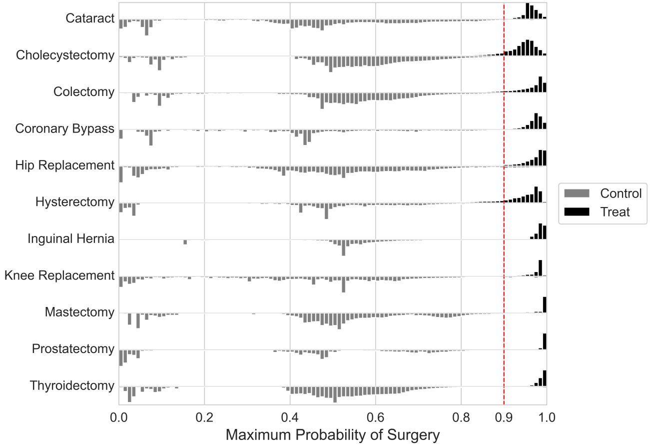
Detection to Treatment: Model performance

Estimate $\mathbb{P}(i \text{ receives surgery } k \mid \mathcal{H}_{it})$

- Gradient-boosting classifier
  - interactions of medical events
- Inputs: cumulative medical histories
  - procedures, diagnoses, drugs

  by visit
- High out-of-sample performance
  - well-calibrated and

  interpretable



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Roadmap

Detection to Treatment: Measuring Wait Times to Surgery

Heterogeneity in Wait Times for Surgery in U.S Private Insurance

Wait Times and Adverse Health Outcomes

Wait Times for Surgeries in the U.S.

Ranking of wait times by surgery follows medical intuition

		Detection to Treatment				Preop. to Treatment	
Surgery	Patients	Pct 25th	Pct 50th	Pct 75th	Fraction without Detectable Wait	Pct 50th	Fraction without Detectable Wait
Kidney Transplant	4,421	625	699	716	0.01	35	0.21
Knee Replacement	127,998	121	354	577	0.05	12	0.20
Prostatectomy	32,428	82	127	302	0.02	10	0.30
Endarterectomy	9,645	23	91	468	0.02	7	0.43
Colectomy	61,725	18	70	265	0.27	7	0.52
Cataract	228,013	23	55	300	0.10	16	0.65
Coronary Bypass	40,046	5	24	396	0.08	3	0.44

Wait Times for Surgeries in the U.S.

Key descriptive properties of wait times (measured via detection to treatment)

- Wait times involve multiple providers with no dominant source of congestion WT Comp
  - → Policies designed to decrease surgical wait need to consider entire network
- Wait times vary systematically across demographics, patients' prior health WT Demog
  - → Men wait on average 21 days less; older/sicker patients wait longer
  - → Use causal design to investigate whether these differences create misallocation
- Wait times vary systematically across health insurance plan types WT Plan
  - → Patients enrolled in HMO wait between 1 and 2 weeks more than PPO patients
  - → Mechanism: patients in plans with "gatekeepers" spend more time waiting for PCP Mech.

Roadmap

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Effect of Wait Times on Health and Spending

$$\textit{Outcome: } y_{ispeft} = \beta_0^{(y)} + \beta_w^{(y)} w_{ispeft} + \beta_{lag}^{(y)} y_i^{lag} + \boldsymbol{x}_i' \boldsymbol{\beta}_x^{(ys)} + \phi_{st}^{(y)} + \psi_{spe}^{(y)} + \theta_{sf}^{(y)} + \epsilon_{ispet}^{(y)} \quad \text{(2nd)}$$

$$\textit{Wait time: } w_{ispeft} = \alpha_0 + \alpha_z z_{ispet} + \alpha_{lag} y_i^{lag} + \boldsymbol{x}_i' \boldsymbol{\alpha}_x^{(s)} + \tilde{\phi}_{st} + \tilde{\psi}_{spe} + \tilde{\theta}_{sf} + \varepsilon_{ispet} \quad \text{(1st)}$$

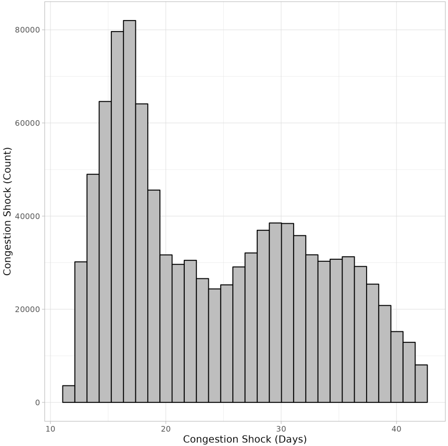
Notes:

- z_{ispet} (our IV): mean wait of other patients seeking care for same {provider type, week, network}
- $\boldsymbol{x}_i$: sex, age group, illness severity
- Fixed effects: year, surgery x month, surgery x insurance plan, surgery x facility type
- y_i^{lag}: patient outcome measured 2-3 years before current episode

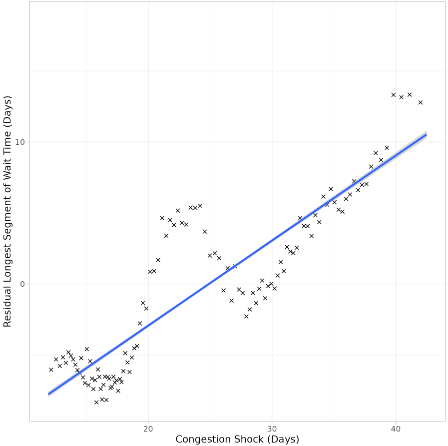
More on IV definition

Effect of Wait Times on Health and Spending: First Stage

"First Stage": variation in wait times from network congestion



(a) Congestion Measure Histogram



(b) Congestion Measure and Waiting Time

1st

Effect of Wait Times on Health and Spending: Second Stage

Dependent Variables:	Total Pay ($)	Inp. Readmission (pct.)	Opioids (days supp.)	Total Pay ($)	Inp. Readmission (pct.)	Opioids (days supp.)
		OLS			IV	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Wait Time 0.9 (days)	1.754***	0.0037***	0.0126***	7.370***	0.0080***	0.0195***
	(0.2798)	(0.0003)	(0.0006)	(1.102)	(0.0013)	(0.0018)
Lag Outcome	Yes	Yes	Yes	Yes	Yes	Yes
Effect +1 Month Wait (pct.)	0.5	0.8	2.1	1.9	1.8	3.2
Outcome Mean	11510.4	13.17	18.1	11510.4	13.17	18.1
Fixed-effects						
Surgery by Year, Month, Plan., Facility Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	662,864	662,864	662,864	662,864	662,864	662,864
R^2	0.19645	0.11709	0.11833	0.19516	0.11658	0.11767
Wald (1st stage), Wait Time 0.9 (days)				2,171.4	2,144.2	2,134.0

Clustered (Surgery-Plan) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

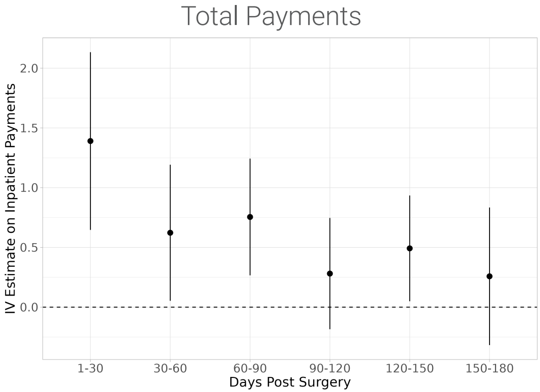
Effect of Wait Times on Health and Spending (continued)

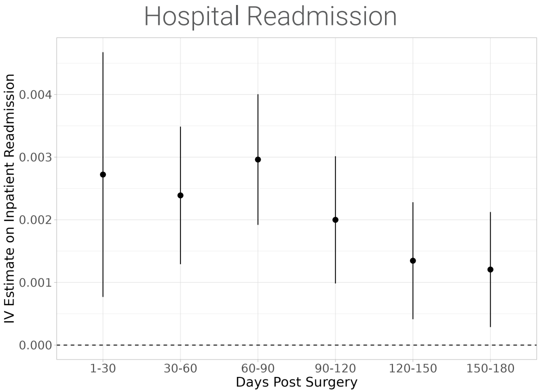
Additional results/robustness

- We also find adverse effects with log instead of levels of wait times Log
  - → Doubling wait time would increase average readmission by 0.8% and opioids by 2.0%
- Adverse effects of wait times are similar or larger when restricting to managed care VS
  - → Provider choice is unlikely to drive the results
- Adverse effects persist long after surgery, especially for opioids
  - → Care decisions made in period surrounding surgery have long-term consequences (Schnell and Currie, 2018)

Effect of Wait Times on Health and Spending (continued)

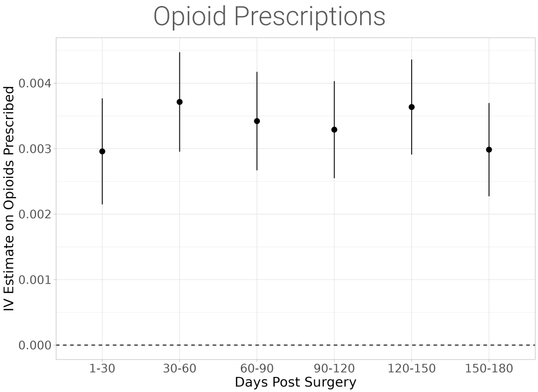
Persistence in outcomes





Effect of Wait Times on Health and Spending (continued)

Persistence in outcomes (continued)



Heterogeneous Effects by Surgery and Patient Characteristics

- Goal: build guidelines that prioritize patient types who suffer most from delays, reducing deadweight loss from waiting (Gravelle and Siciliani, 2008)
- Challenge: many factors can influence adverse effects of wait times

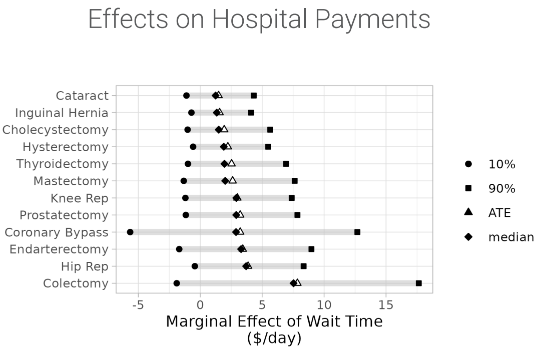
→ Estimate heterogeneous effects using instrumental forests (Athey, Tibshirani, and Wager, 2019)

$$y_{is} = \beta_w^{(y)}(X_{is}) * w_{is} + f^{(y)}(X_{is}) + \epsilon_{is}$$
$$\mathbb{E}[\epsilon|z, X] = 0$$

Validation

Heterogeneous Effects by Surgery and Patient Characteristics

Effects on hospital payments follow medical intuition



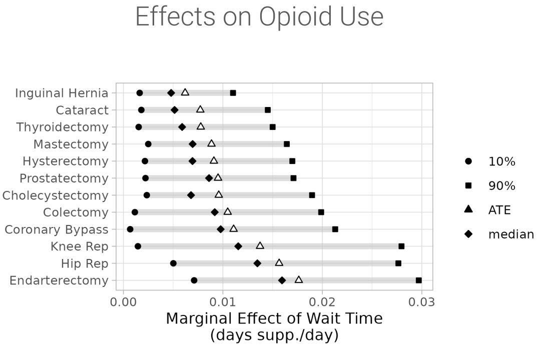
Key observations:

- Heterogeneity across surgeries:
  - → Effects for colectomy are $3\times$ cataract
- Effects largest for specific surgery types
  - → bowel, heart, carotid surgeries
- Large heterogeneity within surgery
  - → heart surgery: 90th effect is $3\times$ $50th$

Validation

Heterogeneous Effects by Surgery and Patient Characteristics

Effects on opioids highlight distinct set of surgeries



Key observations:

- Ranking differs from hospital payments
  - → Orthopedics have larger effects
- Large cohorts have high prescription rates
  - → Can see benefits from lowering waits

Validation

Evaluating Gains from Patient Prioritization

- Simulate outcomes with fixed total wait times ($\approx$ no change in providers' capacity)
- Solve the following allocation problem within surgery:

$$S^{cf} = \frac{1}{|\mathcal{I}_s|} \arg \min_{\boldsymbol{x} \in \{0,1\}^{I \times J}} \sum_{i,j} (x_{ij} w_{js}) * \hat{\beta}(X_{is}) \text{ s.t } \sum_{j} x_{ij} = 1 \text{ and } \sum_{i} x_{ij} = 1$$

+ Solve for same problem with planner reallocating based on coarser $\tilde{\beta}_{is}$ where

$$\tilde{\beta}_{is} = \mathbb{E}[\hat{\beta}_w(X_{is}) | s, age, Charlson, sex]$$

Evaluating Gains from Patient Prioritization

Prioritize using all variables

Change in Hospital Spending under Counterfactual Prioritization: All Variables

Surgery	Colectomy	Coronary Bypass	Knee Rep
Outcome (US$)	14,319	12,067	6,043
N	19891	19555	63965
$\mathbb{E}[w_{is}^{d} * \hat{\beta}_w(X_{is})]$ (US$)	1423	1097	1180
$\mathbb{E}[w_{is}^{cf} * \hat{\beta}_w(X_{is})]$ (US$)	345	62	535
$\Delta\mathbb{E}[w_{is} * \hat{\beta}_w(X_{is})]$ (%)	-75.7	-94.3	-54.6
Δ Outcome (%)	-7.5	-8.6	-10.7
Δw Male (days)	15	13	25
Δw Age Above Median (days)	7	-33	-9
Δw Charlson Above Median (days)	32	-85	-33

+ Reallocation substantially reduces wait-attributable spending on surgical care in hospitals
+ Reallocation reduces overall spending on surgical care in hospitals

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- Waits reallocated across demographics (observed prioritization not optimal)

Evaluating Gains from Patient Prioritization

Prioritize using coarse demographics only

Change in Hospital Spending under Counterfactual Prioritization: Coarse Demographics

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$\mathbb{E}[w_{is}^{cf} * \hat{\beta}_w(X_{is})]$ (US$)	1194	610	1117
$\Delta\mathbb{E}[w_{is} * \hat{\beta}_w(X_{is})]$ (%)	-16.1	-44.4	-5.3
Δ Outcome (%)	-1.6	-4	-1
Δw Male (days)	-1	31	-10
Δw Age Above Median (days)	2	-150	-125
Δw Charlson Above Median (days)	75	-174	-137

+ $ savings smaller but still significant when using coarse demographics to reallocate

Evaluating Gains from Patient Prioritization

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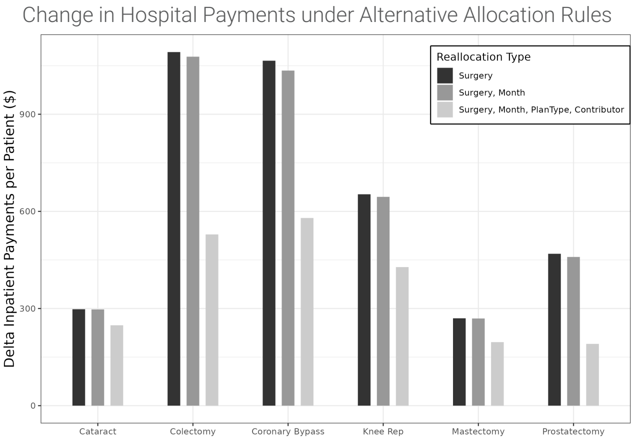
+ more reallocation of waiting times away from high comorbidity patients

Evaluating Gains from Patient Prioritization

Comparing across outcomes



+ Change in hospital payments smaller when reallocation occurs only within plan

Evaluating Gains from Patient Prioritization

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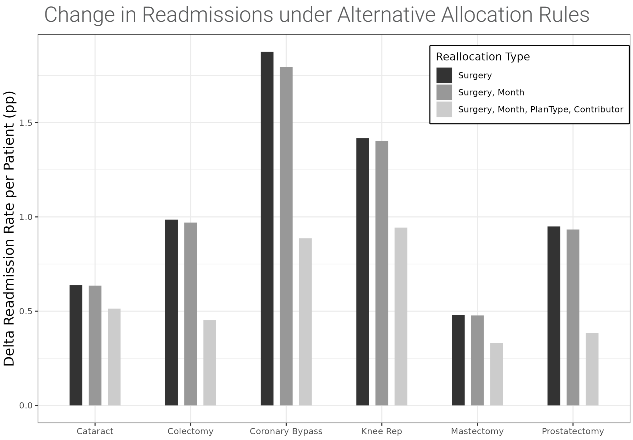
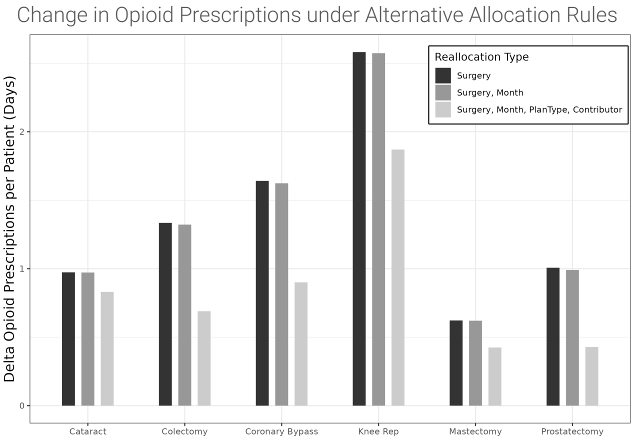


- Change in readmissions smaller when reallocation occurs only within plan

Evaluating Gains from Patient Prioritization

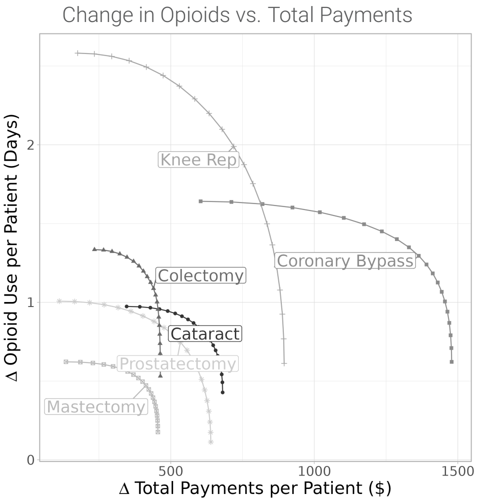
Comparing across outcomes



+ Change in opioid prescriptions smaller when reallocation occurs only within plan

Evaluating Gains from Patient Prioritization

Comparing across outcomes



Conclusion

Develop a measure of wait time using insurance claims

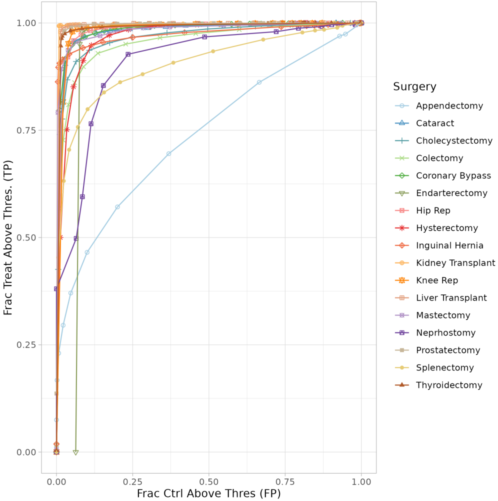
- Measure matches medical intuition
- Permits exploration of heterogeneity in wait times in employer-sponsored insurance

Estimate causal effects of wait times on multiple health and spending outcomes

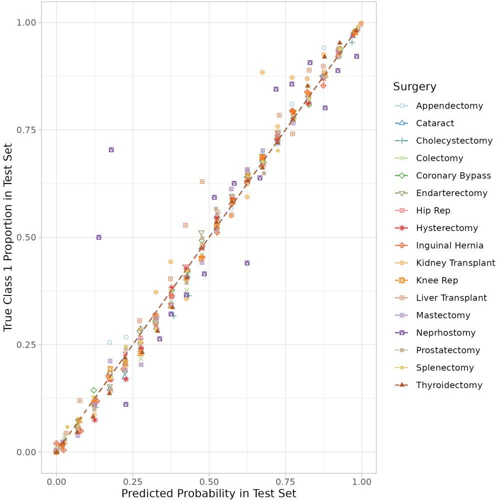
- Adverse effects on hospital outcomes and opioid use (depending on surgery)
- Reallocation exercise suggests efficiency gains from alternative prioritization

Future work: Combine measure with insurance plan and provider choice models to evaluate market-level interventions

Additional Model Performance: Overall TP/FP

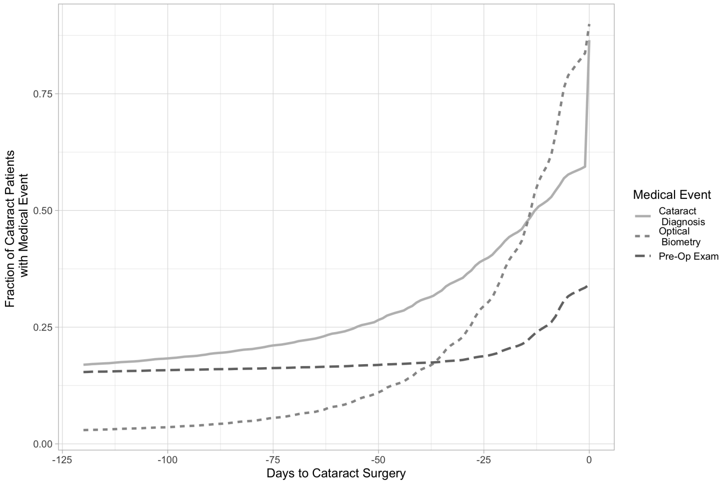


Additional Model Performance: Calibration



Detection to Treatment: Cataract Surgery

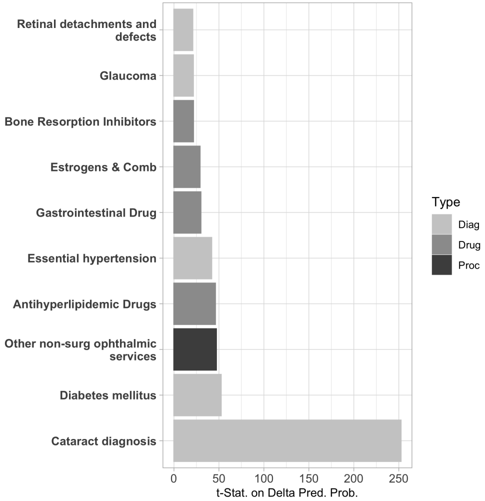
Provider encounters generate medical events



Detection to Treatment: Cataract Surgery

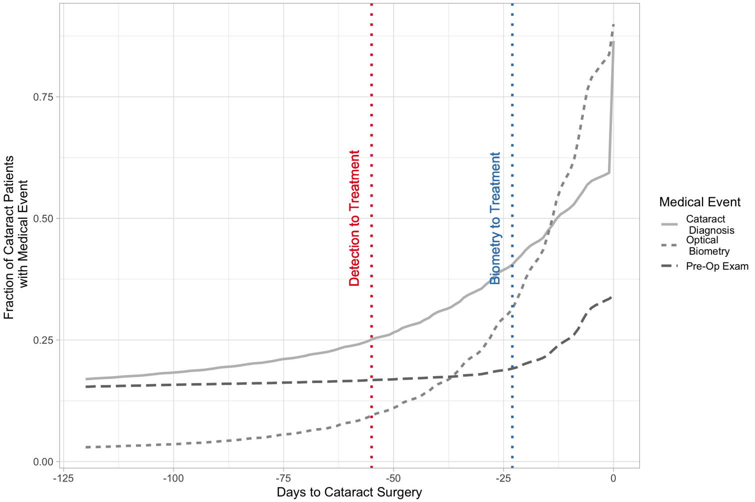
Models learn which medical events predict surgery

- Train models to find predictive events among thousands of predictors
- Combine information from drugs, diagnoses, procedures
- Learn both from chronic conditions and pre-operative trajectory changes

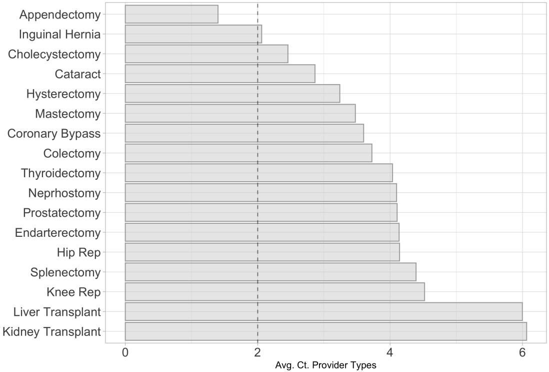


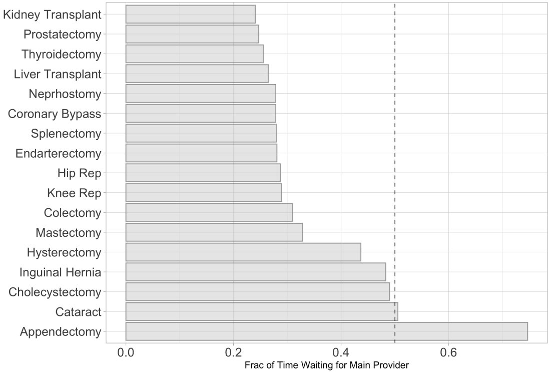
Detection to Treatment: Cataract Surgery

Combination of data elements improves detection



Surgical Wait Times are Decentralized





Back

Heterogeneity in Wait Times Across Demographics

Regress wait times on:

- Patient char. $\boldsymbol{x_i}$ and Plan char. $\boldsymbol{y_p}$
- IV plan char. $\boldsymbol{y_p}$ with employer averages

$$w_{ispt} = \boldsymbol{x}_i'\boldsymbol{\beta_x} + \boldsymbol{y}_{pt}'\boldsymbol{\beta}_p + \phi_{st} + \epsilon_{ispt}$$

Older, sicker patients, and women wait longer

Back

Dependent Variables:	Wait Time (days)	
	IV	
Model:	(No OOP)	(OOP)
Panel A Demographic Variables		
0-17	-9.780***	-9.960***
	(2.821)	(2.777)
18-34	0.6120	0.6205
	(2.036)	(2.047)
45-54	-0.9340	-0.7506
	(1.105)	(1.116)
55-64	7.399***	8.039***
	(1.983)	(1.992)
Charlson Comor. Score	8.132***	8.125***
	(1.596)	(1.595)
Male	-21.29***	-21.52***
	(1.895)	(1.900)
Fixed-effects		
Surg. x Month & Year FE	Yes	Yes
Fit statistics		
Observations	765,167	765,167
R^2	0.22447	0.22527

Heterogeneity in Wait Times Across Health Insurance Designs

Regress wait times on:

- Patient char. $\boldsymbol{x_i}$ and Plan char. $\boldsymbol{y_p}$
- IV plan char. $\boldsymbol{y_p}$ with employer averages

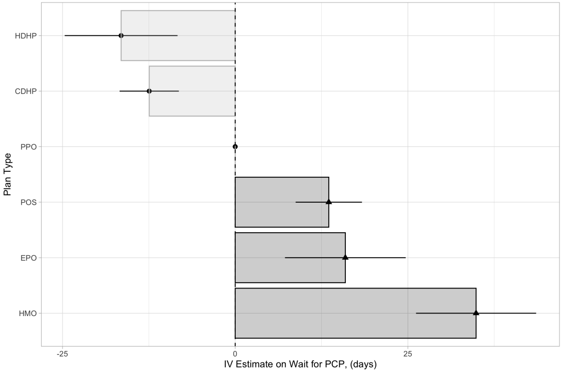
$$w_{ispt} = \boldsymbol{x}_i'\boldsymbol{\beta_x} + \boldsymbol{y}_{pt}'\boldsymbol{\beta}_p + \phi_{st} + \epsilon_{ispt}$$

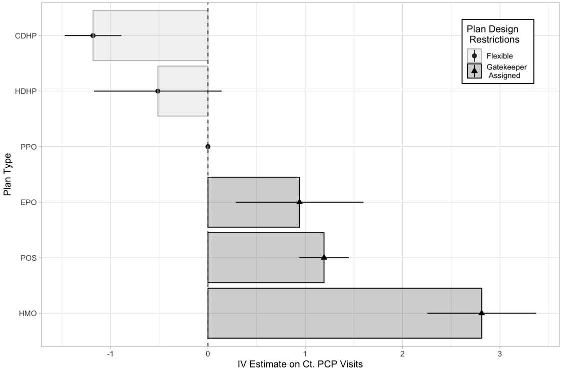
Restrictive plans have longer waits than flexible plans

Back Mech.

Dependent Variables:	Wait Time (days)	
	IV	
Model:	(No OOP)	(OOP)
Panel B: Plan Design Variables		
HMO	12.43***	7.035***
	(2.276)	(1.972)
EPO	-7.682	-15.83**
	(6.687)	(6.559)
POS	-7.468***	-7.473***
	(1.254)	(1.336)
POScap	37.46***	12.06
	(9.887)	(8.311)
CDHP	-4.669*	4.839
	(2.508)	(2.944)
HDHP	-11.27**	2.060
	(5.001)	(4.853)
Comprehensive	-7.871**	-2.955
	(3.509)	(3.278)
Share Out of Pocket		-64.45***
		(6.080)
Fixed-effects		
Surg. x Month & Year FE	Yes	Yes
Fit statistics		
Observations	765,167	765,167
R^2	0.22447	0.22527

Gatekeeping Plan Design Restriction Influence Wait Time





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Instrument: Definition Details

- Group providers: surgeon, specialist, laboratories, PCP, facility, ...
- Define legs in patient history among provider types that contribute to wait time
- Define congestion g_{ipe}^{ℓ} as the average wait time for other patients in plan network in same week, prov. type for patient's longest and last legs
- Define congestion shock $\tilde{g}_{ipe}^{\ell}$ as residual from the following log-linear model:

$$g_{ipe}^{\ell} = \exp\left(\gamma_0 + \gamma_{lag} y_i^{lag} + \boldsymbol{x}_i' \gamma_x^{(s)} + \breve{\phi}_{st} + \breve{\psi}_{spe} + \breve{\theta}_k + \tilde{g}_{ipe}^{\ell}\right)$$

- Final instrument improves precision using $z_{ispe} = \mathbb{E}[w_{ispe} | s_i, \tilde{g}_{ipe}^{long}, \tilde{g}_{ipe}^{last}]$
  - $\rightarrow$ Use cross-fitting and no other covariates to avoid bias

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Instrument Relevance: First Stage

Dependent Variable:	Wait Time 0.9 (days)
Model:	(1)
Variables	
inst_z_pred_wt_combined	1.059***
	(0.0227)
sum_all_pay__lag_1095_730	0.0009***
	(6.86×10^{-5})
Fixed-effects	
Surgery by Year, Month, Plan., Facility Type FE	Yes
Fit statistics	
Observations	662,864
R^2	0.26035
Within Adjusted R^2	0.05721

Clustered (Surgery-Plan) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Instrument Exogeneity: Balance Lag outcomes $y^{lag(-2)}$

	Wait Time			Shock		
	F Stat	P Value	N	F Stat	P Value	N
Cataract	192.242	< 0.001	170641	0.954	0.463	170641
Cholecystectomy	162.981	< 0.001	233330	0.995	0.433	233330
Colectomy	56.817	< 0.001	33094	0.126	0.997	33094
Coronary Bypass	135.702	< 0.001	30529	0.833	0.560	30529
Endarterectomy	21.045	< 0.001	7767	0.739	0.639	7767
Hip Rep	23.588	< 0.001	49944	0.480	0.849	49944
Hysterectomy	23.323	< 0.001	129446	0.964	0.455	129446
Inguinal Hernia	5.773	< 0.001	85969	3.398	0.001	85969
Knee Rep	48.987	< 0.001	98276	0.219	0.981	98276
Mastectomy	101.319	< 0.001	65600	1.138	0.335	65600
Prostatectomy	12.214	< 0.001	21502	0.165	0.992	21502
Thyroidectomy	6.960	< 0.001	26714	0.077	0.999	26714

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Instrument Monotonicity: First Stage by Surgery

Sample	Estimate	Std. Error	P-Value	Observations
Cataract	1.28	0.055	< 0.001	124,046
Cholecystectomy	1.45	0.047	< 0.001	157,874
Colectomy	0.85	0.049	< 0.001	22,929
Coronary Bypass	0.87	0.052	< 0.001	21,346
Endarterectomy	0.5	0.061	< 0.001	5,502
Hip Rep	0.55	0.048	< 0.001	34,982
Hysterectomy	1.02	0.049	< 0.001	87,587
Inguinal Hernia	1.22	0.051	< 0.001	58,070
Knee Rep	0.88	0.057	< 0.001	70,372
Mastectomy	1.01	0.061	< 0.001	46,150
Prostatectomy	0.55	0.064	< 0.001	15,663
Thyroidectomy	0.66	0.048	< 0.001	18,343
Age 0-17	1.37	0.094	< 0.001	9,407
Age 18-34	1.21	0.044	< 0.001	50,164
Age 35-44	1.09	0.032	< 0.001	101,384
Age 45-54	1.01	0.026	< 0.001	188,369
Age 55-64	1.09	0.03	< 0.001	313,540
Charlson 0	1.08	0.024	< 0.001	470,586
Charlson 1+	1.01	0.025	< 0.001	192,278
Female	1.09	0.025	< 0.001	419,582
Male	1.04	0.027	< 0.001	243,282

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Instrument Monotonicity: First Stage by sub-sample

Sample	Estimate	Std. Error	P-Value	Observations
Cataract	1.28	0.055	< 0.001	124,046
Cholecystectomy	1.45	0.047	< 0.001	157,874
Colectomy	0.85	0.049	< 0.001	22,929
Coronary Bypass	0.87	0.052	< 0.001	21,346
Endarterectomy	0.5	0.061	< 0.001	5,502
Hip Rep	0.55	0.048	< 0.001	34,982
Hysterectomy	1.02	0.049	< 0.001	87,587
Inguinal Hernia	1.22	0.051	< 0.001	58,070
Knee Rep	0.88	0.057	< 0.001	70,372
Mastectomy	1.01	0.061	< 0.001	46,150
Prostatectomy	0.55	0.064	< 0.001	15,663
Thyroidectomy	0.66	0.048	< 0.001	18,343
Age 0-17	1.37	0.094	< 0.001	9,407
Age 18-34	1.21	0.044	< 0.001	50,164
Age 35-44	1.09	0.032	< 0.001	101,384
Age 45-54	1.01	0.026	< 0.001	188,369
Age 55-64	1.09	0.03	< 0.001	313,540
Charlson 0	1.08	0.024	< 0.001	470,586
Charlson 1+	1.01	0.025	< 0.001	192,278
Female	1.09	0.025	< 0.001	419,582
Male	1.04	0.027	< 0.001	243,282

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Additional Results: Various Specifications

Dependent Variable:	Total Pay ($)					
	IV					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Wait Time 0.9 (days)	12.18***	13.00***	8.289***	7.370***	6.785***	6.752***
	(1.811)	(1.195)	(1.111)	(1.102)	(1.348)	(1.374)
Patient Controls	No	No	Yes	Yes	Yes	Yes
Lag Outcome	No	No	No	Yes	Yes	Yes
Fixed-effects						
Surgery-Year	Yes	Yes	Yes	Yes	Yes	Yes
Surgery-Month	Yes	Yes	Yes	Yes	Yes	Yes
Surgery-Plan		Yes	Yes	Yes	Yes	Yes
Surgery-Place		Yes	Yes	Yes	Yes	Yes
Provider Type (Longest Leg)					Yes	Yes
Provider Type (Last Leg)						Yes
Fit statistics						
Observations	662,864	662,864	662,864	662,864	662,864	662,864
R^2	0.11757	0.13763	0.19053	0.19516	0.19555	0.19562
Wald (1st stage), Wait Time 0.9 (days)	645.82	2,081.6	2,134.0	2,171.4	2,087.7	2,004.7

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Various Specifications, Managed Care only

Dependent Variable:	Total Pay ($)					
	IV					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Wait Time 0.9 (days)	14.90***	15.38***	10.36***	9.610***	9.038***	8.910***
	(2.432)	(2.310)	(2.123)	(2.105)	(2.543)	(2.576)
Patient Controls	No	No	Yes	Yes	Yes	Yes
Lag Outcome	No	No	No	Yes	Yes	Yes
Fixed-effects						
Surgery-Year	Yes	Yes	Yes	Yes	Yes	Yes
Surgery-Month	Yes	Yes	Yes	Yes	Yes	Yes
Surgery-Plan		Yes	Yes	Yes	Yes	Yes
Surgery-Place		Yes	Yes	Yes	Yes	Yes
Provider Type (Longest Leg)					Yes	Yes
Provider Type (Last Leg)						Yes
Fit statistics						
Observations	234,407	234,407	234,407	234,407	234,407	234,407
R^2	0.09751	0.12114	0.16377	0.16807	0.16852	0.16881
Wald (1st stage), Wait Time 0.9 (days)	701.72	668.65	704.01	731.24	979.73	965.16

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Specification in log Wait Time

Dependent Variables:	Inp. Readmission (pct.)	Inp. Stay (days)	Opioids (days supp.)	Inp. Readmission (pct.)	Inp. Stay (days)	Opioids (days supp.)
		OLS			IV	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
log Wait Time	0.4238***	0.0648***	1.452***	0.8478***	0.1072***	1.966***
	(0.0339)	(0.0050)	(0.0685)	(0.1012)	(0.0153)	(0.1614)
Lag Outcome	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Surgery by Year, Month, Plan., Facility Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	662,864	662,864	662,864	662,864	662,864	662,864
R^2	0.11700	0.08048	0.11785	0.11670	0.08029	0.11763
Wald (1st stage), log Wait Time				4,098.6	4,088.7	4,079.1

Clustered (Surgery-Plan) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Validating Heterogeneous effect model with Calibration

Validating causal model is difficult as there is no natural measure of fit

Calibration approach: use an estimator of the treatment effect to test out-of-sample validity of predicted effects

1. Predict $\hat{\beta}_w(X_i^{test})$ on a hold-out test set
2. Rank and group predicted effects in quantiles $g \in \{1, ..., G\}$
3. Compare $\frac{1}{|g|}\sum_{i \in g} \hat{\beta}_w(X_i^{test})$ to estimate of $\tilde{\beta}_{w\,g} = \frac{\mathbb{E}_g[(y-\mu(x))(z-\rho(x))]}{\mathbb{E}_g[(w-\pi(x))(z-\rho(x))]}$ for all g

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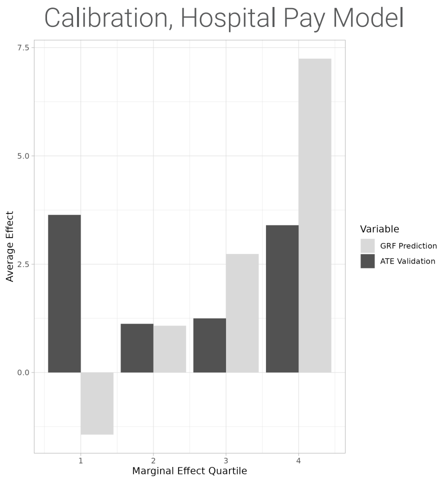
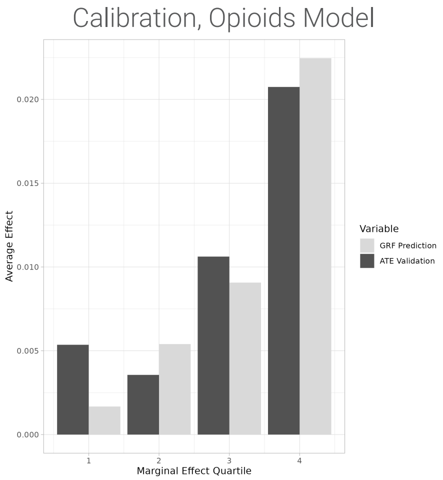
Validating Heterogeneous effect model with Calibration





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