Targeting Overuse of Home Health Care:

Evidence from Multiple Policy Instruments

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Multiple Policy Instruments

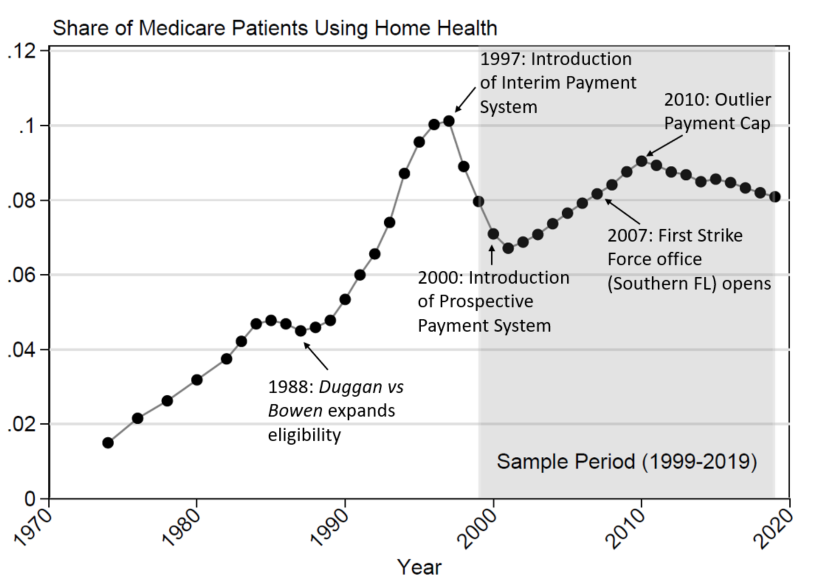
- We often deploy multiple public policies with a common objective
- How might this affect optimal design of each policy?
- We study this issue in the context of Medicare-financed home health care
  - Large and growing part of Medicare
  - Considerable concerns about perceived waste and/or fraud
  - Government has (concurrently) deployed a battery of policies

Medicare home health: medical treatment or consumption good?

"Policymakers have long struggled to define the role of the home health benefit in Medicare... From the outset, there was a concern that setting a narrow policy could result in beneficiaries using other, more expensive services, while a policy that was too broad could lead to wasteful or ineffective use of the home health benefit."

– Medicare Payment Advisory Commission, 2020

Medicare Home Health Appears Highly Responsive to Policy Changes



Overview

Study three recent policies with common aim of reducing wasteful home health care

- Geographically-targeted strike forces prosecuting fraud (2007-2013)
- Geographically-targeted moratoria on entry of new home health agencies (2013-2016)
- Nationwide cap on certain Medicare home health payments (2010)

Empirical framework:

- Medicare claims data (1999-2019)
- Exploit variation in timing and spatial application to study impacts

Rare opportunity to study impacts of different combinations of policies with a common objective

- Depending on location and time period, anywhere from no policies to three policies in effect

Summary of Findings (Preliminary!!!)

Average impact of each policy:

- Each policy reduces home health use by 20-30%
- No evidence that policy-induced reductions in home health cause substitution to nursing homes

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Counterfactual targeting of policies:

- Estimate heterogeneous treatment effects using causal forest
- Geographically-focused policies were targeted at areas with higher-than-average treatment effects
- However, optimal geographic targeting could have more than doubled savings [**preliminary**]

Related Literature

Optimal targeting of policies:

- On observables (e.g. Kitigawa and Tetenov 2018; Athey and Wager 2021, Johnson et al 2023), unobservables (e.g. Einav et al. 2022; Ito et al., 2023) or both (Ida et al. 2022)
- Key theme: target on treatment effects rather than outcomes
- This paper: with multiple policies, target on *incremental* not gross treatment effects

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Waste in U.S. health care:

- Health care spending is one-fifth of the economy, and half is taxpayer financed
- Consensus that there is a lot of waste, but hard to find effective policies
- We identify three effective policies

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Medicare home health

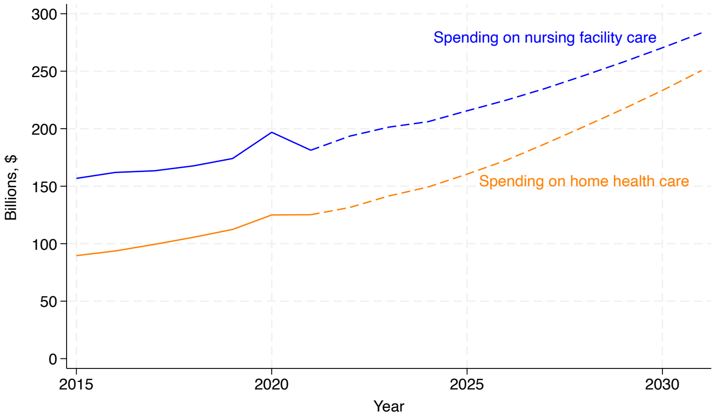
- Lack of substitution to nursing care (Kemper 1988; McKnight 2006)
- Work on strike forces (O'Malley et al. 2023) and outlier cap (Kim and Norton 2015)

Outline

- Setting and data
- Average policy impacts on home health and nursing home care
- Heterogeneous policy impacts
- Counterfactual policy placement and optimal geographic targeting

Setting and Data

Total US Spending on Home Health and Nursing Facility Care



- ▷ About 2/3 of home and nursing care publicly financed
- ▷ Medicare pays for about 1/2 of publicly-financed care

Medicare Home Health

Looms large:

- Used by one-in-twelve Medicare enrollees 65+ (*one in five* 85+)
- Spending: $20 billion per year, 30% of Medicare spending on post-acute care

Eligibility:

- Must have difficulty leaving home without considerable effort
- Must require part-time or intermittent skilled care (for a time-limited basis)
- Eligibility re-certified at least every 60 days

Services:

- Skilled nursing, physical therapy, speech-language, occupational therapy, home health aides

Payment:

- Medicare pays based on case-mix adjusted prospective-payment system
- Median 60-day episode: 24 visits, about $180/visit

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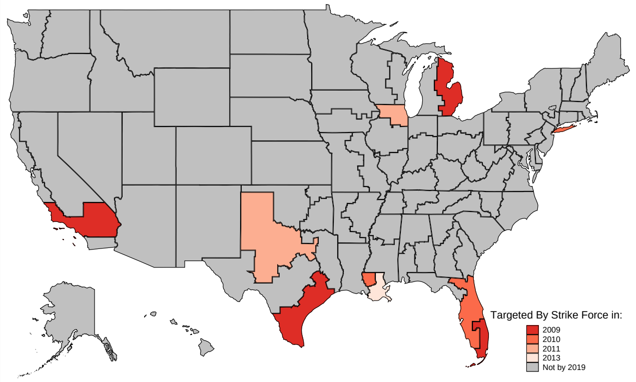
- ▷ Median 60-day episode: 24 visits, about $180/visit
- ▷ **[NOTE]** No patient cost-sharing

Three overlapping, related policies

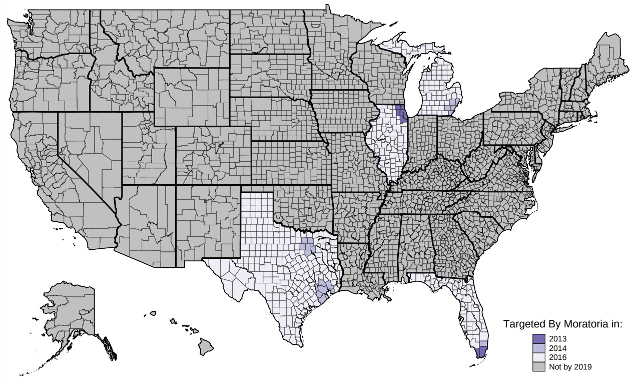
- Geographically-targeted strike forces prosecuting fraud (2007-2013)
- Geographically-targeted moratoria on entry of new home health agencies (2013-2016)
- Nationwide cap on certain Medicare home health payments (2010)

Medicare Home Health Policy Reforms: Strike Forces



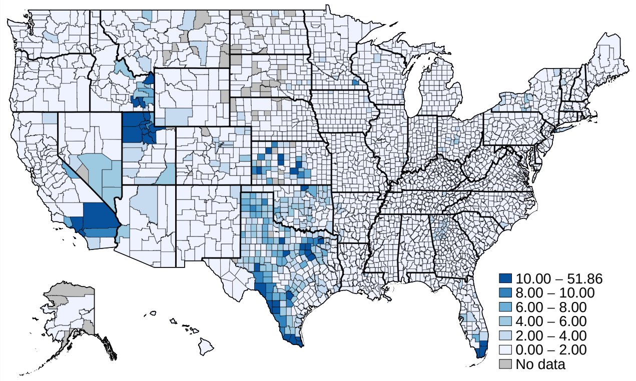
- Joint between DOJ and HHS-OIG
- Targets prosecutable fraud
- Started 2007 in Southern Florida
  - 10 districts by 2013
- Districts chosen based on:
  - Aberrant billing patterns
  - Intelligence on potential fraud
- By 2018: Over 2,400 cases against 600 defendants for $\sim$\$2 billion in losses
- By far the most resource-intensive of the three policies

Medicare Home Health Policy Reforms: Home Health Agency Moratoria



- Also joint between DOJ and HHS-OIG
- Started in 2013 in counties with high growth in HHA entry:
  - Chicago, IL
  - Miami, FL
  - Houston, TX
  - Fort Lauderdale, FL
  - Detroit, MI
  - Dallas, TX
- Expanded in 2016 to all counties in those four states (FL, IL, TX, MI)
- 70% overlap with Strike Force
  - Will account for in analysis

Medicare Home Health Policy Reforms: Outlier Payment Cap (Nationwide)



- Announced 2009, implemented 2010
- Outlier payments **capped at 10%** of total payments to HHA each year
  - Outlier payment: additional payments for patient episodes with usually high levels of services
  - No outlier payments beyond cap
- Empirical strategy: variation in "bite": county's outlier payment share to reform

	Mean	75th Pctile	Above 10%: Share	Above 10%: Mean
All	2.19	1.57	6.6%	18.34
SF or M	5.40	7.07	21.3%	18.60
Neither SF or M	0.93	0.86	0.8%	15.50

Data

Data:

- 20% random sample of Traditional Medicare beneficiaries 1999-2019
  - Limit to beneficiary-years enrolled in TM for entire year
- Master Beneficiary Summary File:
  - Patient demographics, zip code of residence, race, gender
  - Annual health care utilization by category
- Home Health Claims
  - Start and end dates of each episode of care
  - HHA that provides care
  - Visits and payments
  - Amount of outlier payments

Summary Statistics

	All	Strike Force		Moratorium		Outlier Payment Share	
		Yes	No	Yes	No	Above Median	Below Median
County Average (2007)							
HH Visits Per Capita	3.08						
HH Payments Per Capita	$419						
Share of Patients Using HH	0.093						
Average Change (2003-2007)							
HH Visits Per Capita	0.85						
HH Payments Per Capita	$147						
Share of Patients Using HH	0.014						
Number of Counties	3,177						

Summary Statistics

	All	Strike Force		Moratorium		Outlier Payment Share	
		Yes	No	Yes	No	$\geq$ 75th Pctile	$<$ 75th Pctile
County Average (2007)							
HH Visits Per Capita	3.08	5.76	2.27	5.69	2.31	4.82	2.08
HH Payments Per Capita	$419	$738	$322	$725	$328	$586	$323
Share of Patients Using HH	0.093	0.131	0.082	0.130	0.083	0.110	0.084
Average Change (2003-2007)							
HH Visits Per Capita	0.85	2.64	0.31	2.92	0.24	1.88	0.26
HH Payments Per Capita	$147	$349	$86	$382	$77	$246	$90
Share of Patients Using HH	0.014	0.030	0.009	0.036	0.008	0.020	0.011
Number of Counties	3,177	273	2,904	506	2,671	803	2,374

Policy Impacts

Strike Forces and Moratoria

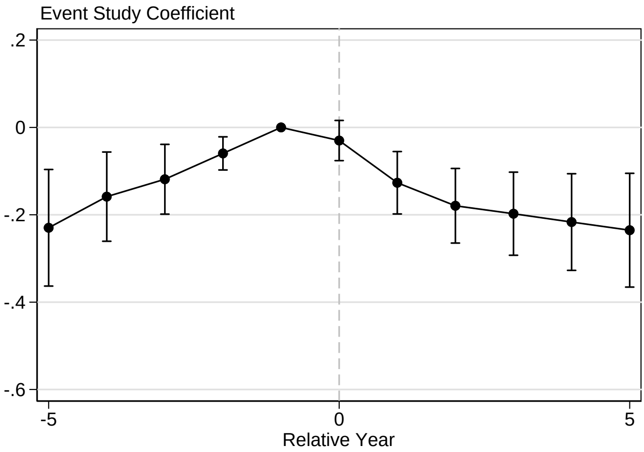
Start by considering the following standard event study for county c in year t:

$$y_{ct} = \alpha_c + \tau_t + \sum_{r \neq -1} \beta_r SF_{cr} + \sum_{\tilde{r} \neq -1} \theta_{\tilde{r}} M_{c\tilde{r}} + \epsilon_{ct}$$

- α_c county fixed effects, τ_t calendar year fixed effects
- SF_{cr}: Indicator that Strike Force office is open in county c in relative year r
- $M_{c\tilde{r}}$: Indicator that moratorium is in county c in relative year $\tilde{r}$

County-years weighted by 2006 Traditional Medicare enrollees, SEs clustered at district level

Strike Force Estimates: Log Home Health Visits Per 100 Enrollees



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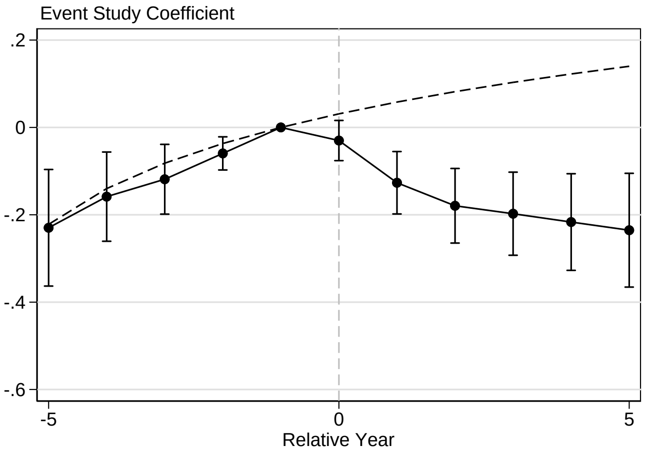

Methods

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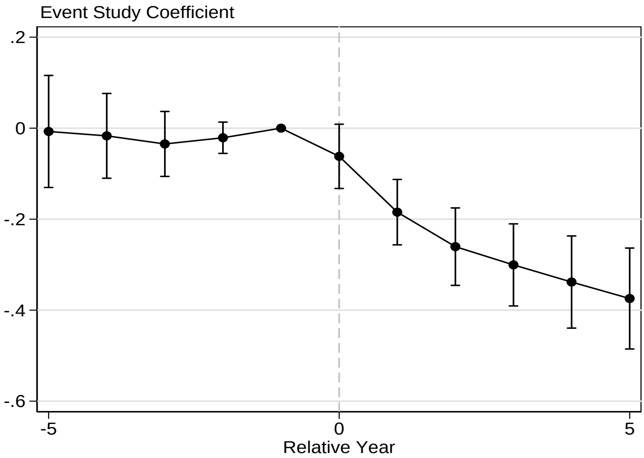
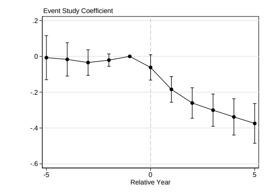


Strike Force and Moratorium: Baseline Estimates

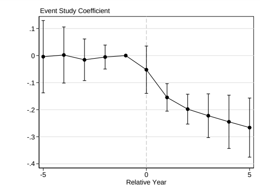
Strike Force

(a) HH Visits Per 100 Enrollees



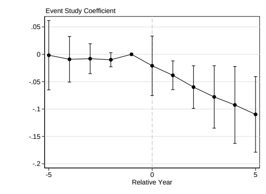
↓ 29.2 percent (se 4.1)

(b) HH Payments Per 100 Enrollees



↓ 21.7 percent (se 3.4)

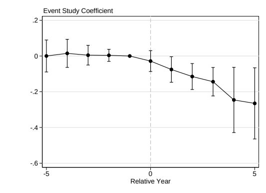
(c) Percent Enrollees Using HH



↓ 7.6 percent (se 2.5)

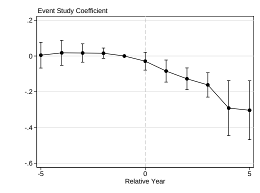
Moratorium

(d) HH Visits Per 100 Enrollees



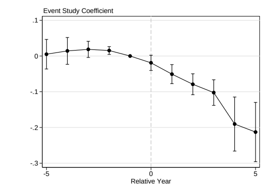
↓ 16.9 percent (se 5.9)

(e) HH Payments Per 100 Enrollees



↓ 19.4 percent (se 4.9)

(f) Percent Enrollees Using HH



↓ 12.7 percent (se 2.3)

▸ Log Trend

Outlier Payment Cap Policy

- Implemented nationwide in 2010
- Empirical strategy: compare counties more vs less affected
- s_j: percent of HHA j's total payments from outlier payments in 2009
- s_c: weighted average of s_j for all HHAs serving patients in county c in 2009
  - weights are share of HH episodes received by patients in county c provided by HHA j in 2009
  - s_c **is the "bite" of the policy**

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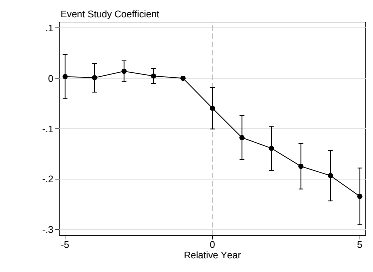
  - **s_c is the "bite" of the policy**

- We parameterize the outlier cap as a binary treatment O_c
  - $O_c = 1$ if $s_c >$ 75th percentile across counties
- Continuous treatment generates very similar results

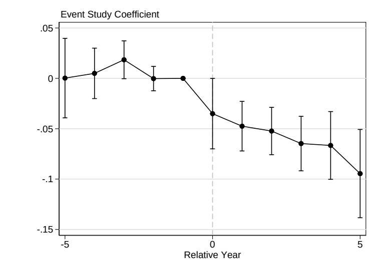
Outlier Payment Cap: Baseline Estimates

(a) Home Health Visits Per 100 Enrollees



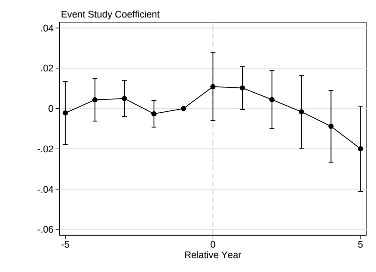
↓ 17.2 percent (se 2.3)

(b) Home Health Payments Per 100 Enrollees



↓ 6.5 percent (se 1.4)

(c) Percent Enrollees Using Home Health



↓ 0.3 percent (se 0.8)

▸ Regression ▸ Log Trend

Home Care - Nursing Home Substitution

Medicare-financed home health is considered a lower-cost substitute for skilled nursing care.

Does the large reduction in home health result in substitution toward skilled nursing care?

We find no evidence of substitution:

- Using above reduced form policy estimation with skilled nursing care as outcome
- Using IV approach: effect of home health use on skilled nursing use, using policies as instruments

Details

Home Care - Nursing Home Substitution: IV Estimates

	All Patients	High Predicted SNF Use	SNF Qualifiers
Effect of HH Visits Per Capita on SNF Covered Days Per Capita			
$\boxed{\text{OLS} \quad 0.0120}$			
	(0.0060)		
IV (Poisson)	0.0039		
	(0.0146)		
IV (Linear)	0.0006		
	(0.0095)		
F-S F Statistic	282.6		
Effect of HH Payments Per Capita on SNF Payments Per Capita			
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IV (Poisson)	0.0467		
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F-S F Statistic	252.9		
N	63,270		

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IV (Linear)	-0.0179		
	(0.0820)		
F-S F Statistic	252.9		
N	63,270		

Home Care - Skilled Nursing Substitution: IV Estimates

	All Patients	High Predicted SNF Use	SNF Qualifiers
Effect of HH Visits Per Capita on SNF Covered Days Per Capita			
OLS	0.0120	-0.0085	-0.1053
	(0.0060)	(0.0075)	(0.0358)
IV (Poisson)	0.0039	-0.0230	-0.0773
	(0.0146)	(0.0468)	(0.1334)
IV (Linear)	0.0006	-0.0383	-0.0833
	(0.0095)	(0.0341)	(0.1526)
F-S F Statistic	282.6	84.7	47.4
Effect of HH Payments Per Capita on SNF Payments Per Capita			
OLS	0.0770	0.0735	-0.3406
	(0.0341)	(0.0545)	(0.1718)
IV (Poisson)	0.0467	-0.1259	-0.6213
	(0.0799)	(0.1985)	(0.4992)
IV (Linear)	-0.0179	-0.4410	-1.5547
	(0.0820)	(0.3694)	(1.5826)
F-S F Statistic	252.9	67.2	83.2
N	63,270	62,608	63,168

- High predicted SNF use:
  - Top 5%
- SNF-qualifying:
  - Inpatient stay lasting 3+ days within 30 days

Counterfactual Policy Placement

Optimal Geographic Targeting

- Aggregate effects:
  - All three policies substantially reduced home health care use
  - No evidence of substitution to skilled nursing care
- But heterogeneity in effects could be important for counterfactuals:
  - What would happen if we expanded strike force and moratoria to un-targeted areas?
  - Holding constant the budget for each policy, can we improve targeting of policies individually or in combination?
- We therefore **estimate heterogeneous treatment effects** of each policy across patients and use them for counterfactuals
  - **Two key assumptions:**
    - Relationship between observables and treatment effects apply out of sample
    - (Will relax) For counterfactuals, assume combined impact of multiple policies is the max of the policy-specific treatment effects for that individual
  - **Caveat:** currently estimating heterogeneous treatment effects for three *policies*; ultimately will estimate heterogeneous treatment effects for seven policy *combinations*

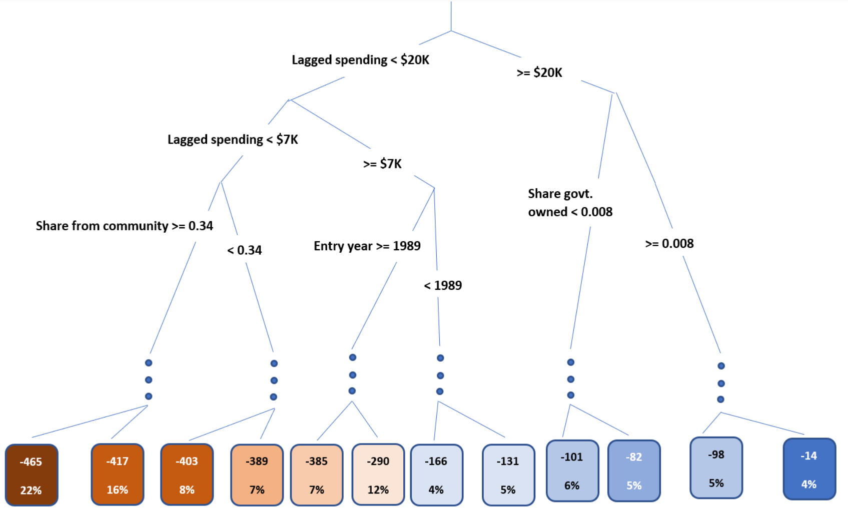
Estimating Heterogeneous Treatment Effects

- Apply the causal forest framework of Athey et al. (2019) to estimate heterogeneous treatment effects of each policy
- Uncover heterogeneity in causal effects by optimally splitting data along a set of chosen covariates in order to maximize differences in treatment effects across splits while guarding against over-fitting
- Grow 250 trees. For each tree:
  - Randomly select half the data, and split the data by covariates to maximize treatment effect heterogeniety across the resulting leaves
  - Then implement those splits in the second half of the data and calculate treatment effects for each leaf ('honest causal forest')
- Treatment effect for each patient is average across 250 trees ('noisy bootstrap' for standard errors)

Enrollee-level features of the causal forest

- Policies are targeted at HHAs, but most enrollees not associated with an HHA
  - therefore for each enrollee, calculate the patient-weighted average characteristic of HHAs used by patients in their zip code in 2006
- Characteristics of HHAs:
  - year founded
  - share of patients from community
  - growth rate of patients from 2004 to 2009
  - whether for-profit, non-profit, or government-owned
- Characteristics of patients:
  - Medicare spending from previous year
  - comorbidities (up to 20)

Causal Forest Algorithm: Hypothetical Tree



Heterogeneous Treatment Effects: Estimates

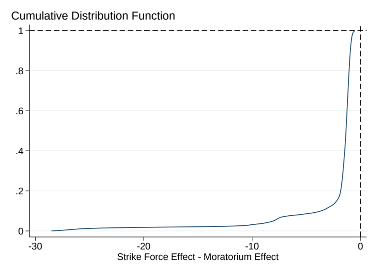
	Effect on Visits			Effect on Payments		
Statistic	Strike Force	Moratorium	Outlier Cap	Strike Force	Moratorium	Outlier Cap
Mean	-2.431	-0.074	-1.175	-171.822	-62.963	-68.503
SD	4.418	0.847	6.849	309.045	106.407	452.367

Var Importance

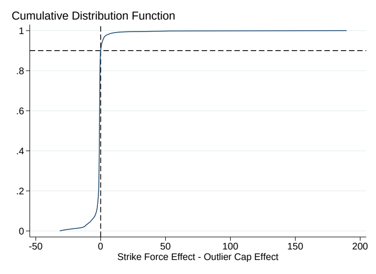
Correlates

CDF of Treatment Effect Differences: HH Visits

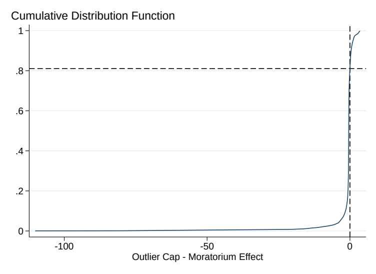
(a) Strike Force - Moratorium



(b) Strike Force - Outlier Cap



(c) Outlier Cap - Moratorium



	Strike Force	Moratorium	Outlier Cap
Mean Effect on Visits	-2.431	-0.074	-1.175

CDF of Treatment Effect Differences: HH Payments

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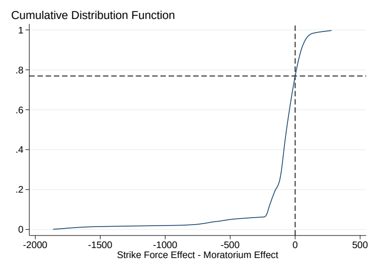

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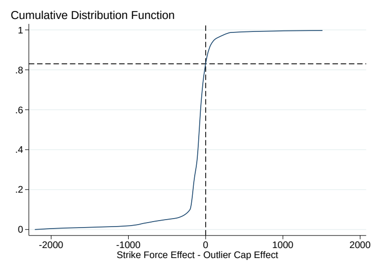

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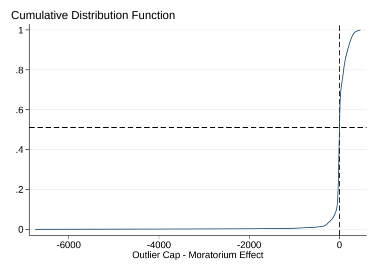

	Strike Force	Moratorium	Outlier Cap
Mean Effect on Payments	-171.822	-62.963	-68.503

Per Capita Effects on Affected vs Unaffected Areas

	Strike Force Effect On:		Moratorium Effect On:	
Counterfactual Area Applied	HH Visits	HH Payments	HH Visits	HH Payments
Homogeneous Effect	-2.82	$-246.50	-0.36	$-100.97
	(1.09)	($57.05)	(0.30)	($39.53)
Affected Areas	-2.96	$-196.00	-0.17	$-88.38
Unaffected Areas	-2.28	$-164.79	-0.05	$-55.68
Entire US	-2.43	$-171.82	-0.07	$-62.96

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Per Capita Savings Under Actual & Counterfactual Policy Implementations

	Actual Placement		Optimal Placement		
Policy Regime	Outlier Cap	No Outlier Cap	Outlier Cap	No Outlier Cap	Cost
Baseline	$-68.48	$0.00	$-68.48	$0.00	$0.00
+ Strike Force	$-24.04	$-44.17	$-44.55	$-51.36	$9.61
+ Moratorium	$-12.98	$-19.68	$-17.52	$-24.46	$0.00
+ Strike Force, Moratorium	$-30.05	$-53.06	$-68.63	$-82.34	$9.61

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Patient and HHA Attributes Under Actual and Optimal Targeting of Strike Force

		Optimal	
	Actual	No Outlier Cap	Outlier Cap
Characteristic	(1)	(2)	(3)
2006 HH Visits Per Capita	4.70	4.74	2.96
2006 HH Payments Per Capita	$611	$565	$398
2009/2004 HH Visits Per Capita	1.75	1.45	1.26
2009/2004 HH Payments Per Capita	1.96	1.64	1.53
HHA Entry Year	1994	1986	1982
Share of Patients from Community	0.70	0.67	0.64
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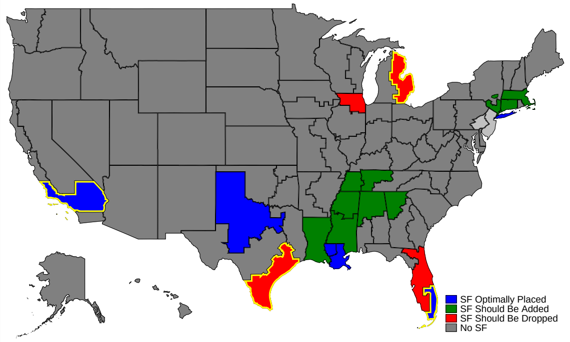
Optimal Placement of Strike Force

(a) Without Outlier Cap



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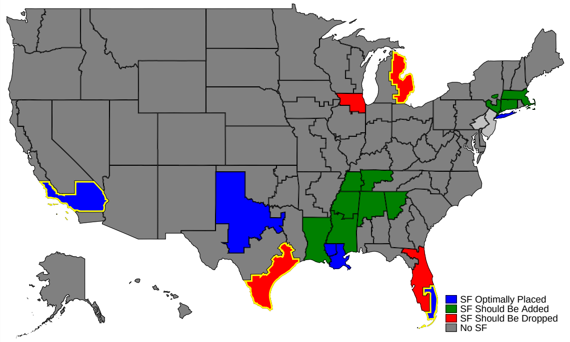
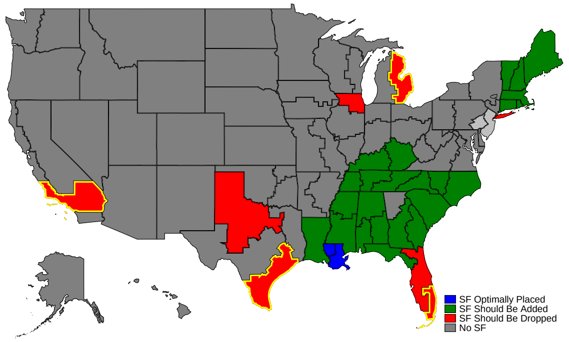


(b) With Outlier Cap



Conclusions

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- We studied three very different policy instruments for combating waste in Medicare-financed home health care
- Current findings are **still preliminary!!**
- Each policy reduces home health by 20 to 30 percent
- No evidence of substitution toward skilled nursing care
- Important to consider overlaps in policies:
  - Optimal placement of strike force and moratorium varies by presence of outlier cap
  - Optimal geographic targeting could more than double their impact
- Results underscore value of coordination across policies pursuing similar objectives

Thank You!

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Strike Forces and Moratoria: Baseline Specification

$$\tilde{y}_{ct} = \alpha + \sum_{r \neq -1} \beta_r SF_{cr} + \sum_{\tilde{r} \neq -1} \theta_{\tilde{r}} M_{c\tilde{r}} + \epsilon_{ct}$$

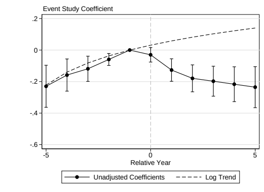
- $\tilde{y}_{ct} = y_{ct} - \hat{y}_{ct}$
- $\hat{y}_{ct} = \hat{\alpha}_c + \hat{\tau}_t + \hat{\gamma} \log R_{cr} + \hat{\phi} \log \tilde{R}_{c\tilde{r}}$, i.e. estimated outcome absent the policies under logarithmic growth

Strike Force and Moratorium Estimates: Log Trend

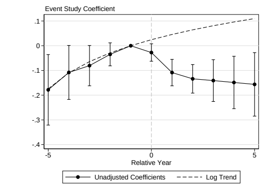
◂ Back

Strike Force

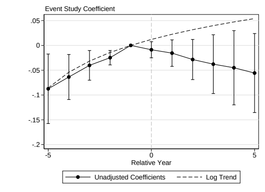
(a) HH Visits Per 100 Enrollees



(b) HH Payments Per 100 Enrollees

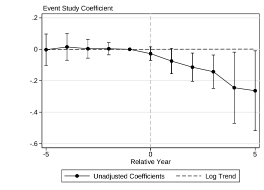


(c) Percent Enrollees Using HH

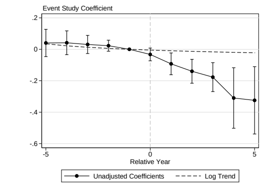


Moratorium

(d) HH Visits Per 100 Enrollees



(e) HH Payments Per 100 Enrollees



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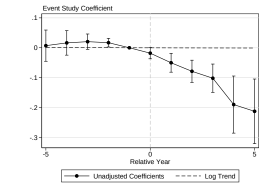


Detrending Event Study Specification

Back

- Estimate:

$$y_{ct} = \alpha_c + \tau_t + \sum_{r \notin \Omega} \beta_r SF_{cr} + \gamma \log(R_{cr}) + \sum_{\tilde{r} \notin \Omega} \theta_{\tilde{r}} M_{cr} + \phi \log(\tilde{R}_{c\tilde{r}}) + \epsilon_{ct}$$

  where Ω denotes relative years -5 to -1, omitted in order to estimate pretrends γ and ϕ

- Form predicted outcome in absence of reform:

$$\hat{y}_{ct} = \hat{\alpha}_c + \hat{\tau}_t + \hat{\gamma} \log(R_{cr}) + \hat{\phi} \log(\tilde{R}_{c\tilde{r}})$$

- Let $\tilde{y}_{ct} \equiv y_{ct} - \hat{y}_{ct}$
- Our main estimating equation is therefore:

$$\tilde{y}_{ct} = \alpha + \sum_{r \neq -1} \beta_r SF_{cr} + \sum_{\tilde{r} \neq -1} \theta_{\tilde{r}} M_{c\tilde{r}} + \epsilon_{ct}$$

IV Estimates of Nursing Home Substitution

Back

Nonlinear first stage

$$h_{ct} = \exp\left(\alpha_c + \tau_t + \sum_{r \notin \Omega} \beta_r SF_{cr} + \gamma \log(R_{cr}) + \sum_{\tilde{r} \notin \Omega} \theta_{\tilde{r}} M_{c\tilde{r}} + \phi \log(\tilde{R}_{c\tilde{r}}) + \sum_{t \notin \Omega} \delta_t b_{ct} + \psi \log(\bar{R}_t) b_c\right)$$

Second stage

$$s_{ct} = \alpha_c + \tau_t + \rho \hat{h}_{ct} + \gamma \log(R_{cr}) + \phi \log(\tilde{R}_{c\tilde{r}}) + \psi \log(\bar{R}_t) b_c + \epsilon_{ct}$$

Outlier Payment Cap Policy: Baseline Specification

Back

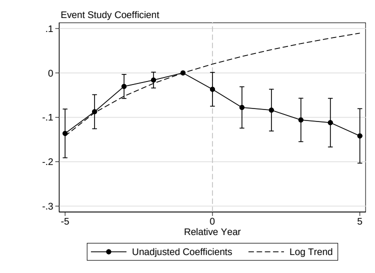
$$\tilde{y}_{ct} = \alpha + \sum_{t \neq -2009} \beta_t O_{ct} + \epsilon_{ct}$$

- O_{cr}: outlier cap "bite" above 75th percentile in county c in relative year r
- $\tilde{y}_{ct} = y_{ct} - \hat{y}_{ct}$
- $\hat{y}_{ct} = \hat{\alpha}_c + \hat{\tau}_t + \hat{\gamma} \log(R_t)$

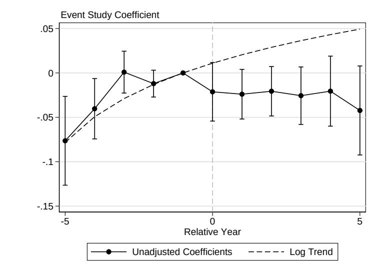
Outlier Payment Cap Estimates: Log Trend

Back

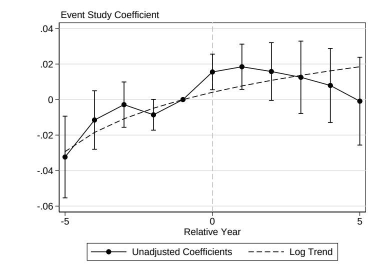
(a) Home Health Visits Per 100 Enrollees



(b) Home Health Payments Per 100 Enrollees



(c) Percent Enrollees Using Home Health



Heterogeneous Treatment Effects: Variable Importance

Back

	Effect on Visits			Effect on Payments		
Covariate	Strike Force	Moratorium	Outlier Cap	Strike Force	Moratorium	Outlier Cap
HHA Entry Year	0.251	0.179	0.247	0.088	0.204	0.110
Average Share of Patients From Community	0.081	0.053	0.085	0.080	0.032	0.124
Share of For-Profit HHAs	0.018	0.017	0.033	0.029	0.014	0.021
Share of Non-Profit HHAs	0.010	0.008	0.016	0.020	0.013	0.011
Share of Government HHAs	0.013	0.014	0.006	0.021	0.011	0.008
Average 2009/2004 HHA Patient Ratio	0.010	0.018	0.008	0.023	0.054	0.011
Lagged Patient Spending	0.554	0.525	0.542	0.651	0.505	0.661
Patient Comorbidities	0.063	0.185	0.063	0.088	0.166	0.054

Heterogeneous Treatment Effects: Correlates

◂ Back

	Effect on Visits		
Covariate	Strike Force	Moratorium	Outlier Cap
HHA Entry Year	-0.451	-0.084	-1.259
	(0.113)	(0.017)	(0.515)
Average Share of Patients From Community	-0.757	-0.125	-1.098
	(0.077)	(0.011)	(0.413)
Share of For-Profit HHAs	-0.579	-0.110	-1.014
	(0.085)	(0.013)	(0.390)
Share of Non-Profit HHAs	0.572	0.108	0.966
	(0.085)	(0.014)	(0.382)
Share of Government HHAs	0.029	0.009	0.200
	(0.026)	(0.004)	(0.071)
Average 2009/2004 HHA Patient Ratio	-0.170	-0.027	-0.294
	(0.035)	(0.006)	(0.184)
Lagged Patient Spending	-3.194	-0.662	-1.615
	(0.149)	(0.016)	(0.592)
Patient Comorbidities	-1.630	-0.468	-0.891
	(0.069)	(0.010)	(0.343)