What's in a Bill?
A Model of Imperfect Moral Hazard in Healthcare

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Motivation: Why Should Patients Share Costs?

Imperfect information (theoretically) justifies **patient cost-sharing**

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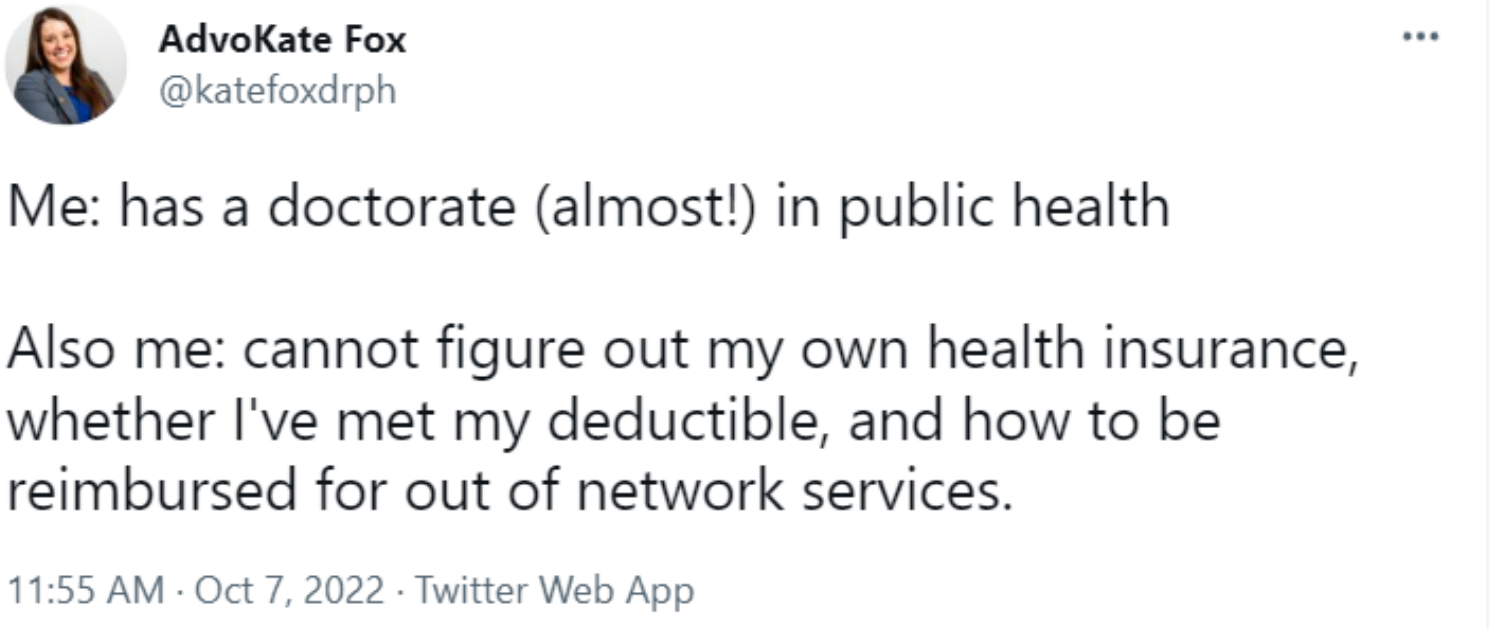
Have I met my deductible?



AdvoKate Fox
@katefoxdrph

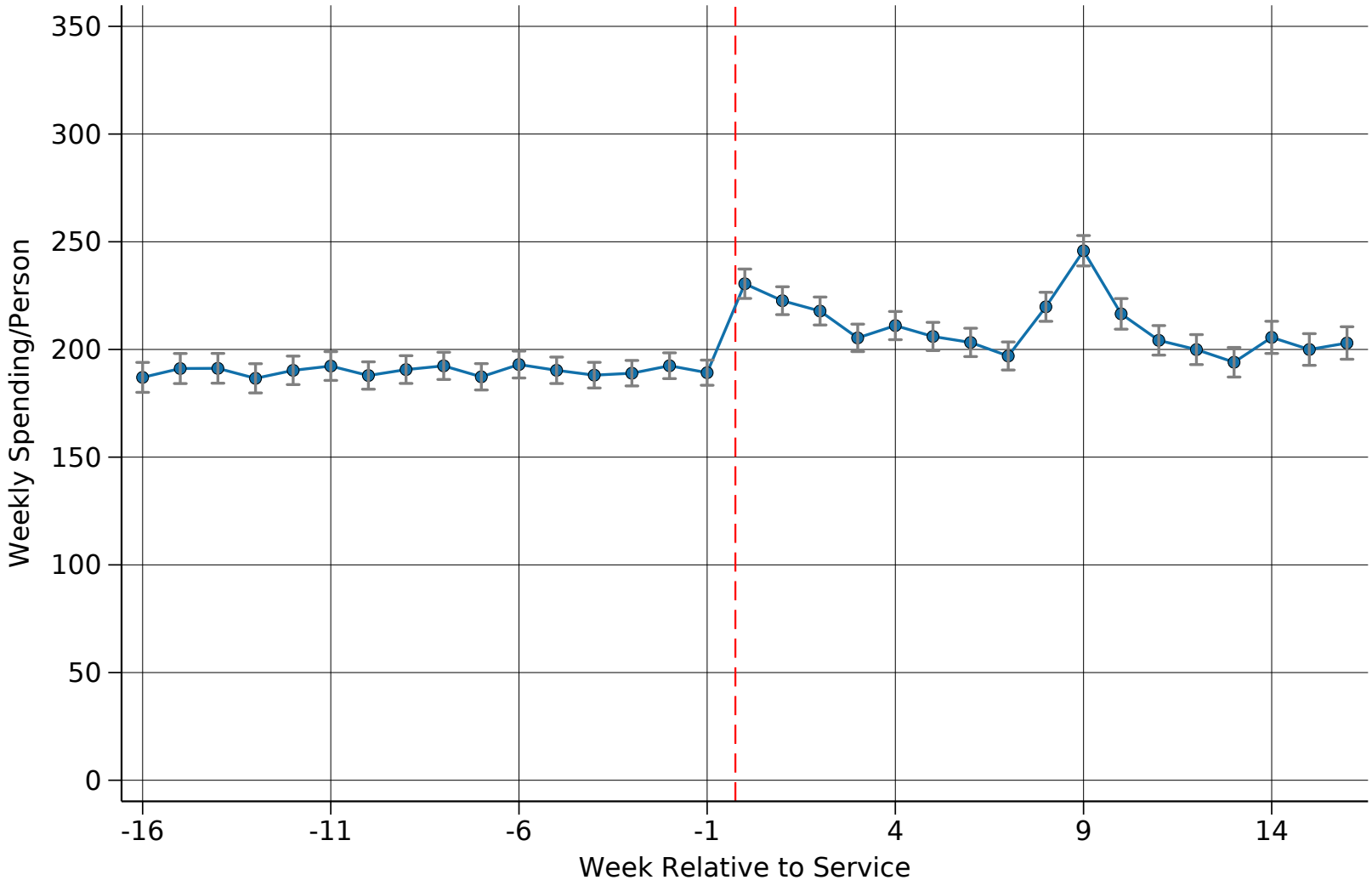
Me: has a doctorate (almost!) in public health

Also me: cannot figure out my own health insurance, whether I've met my deductible, and how to be reimbursed for out of network services.

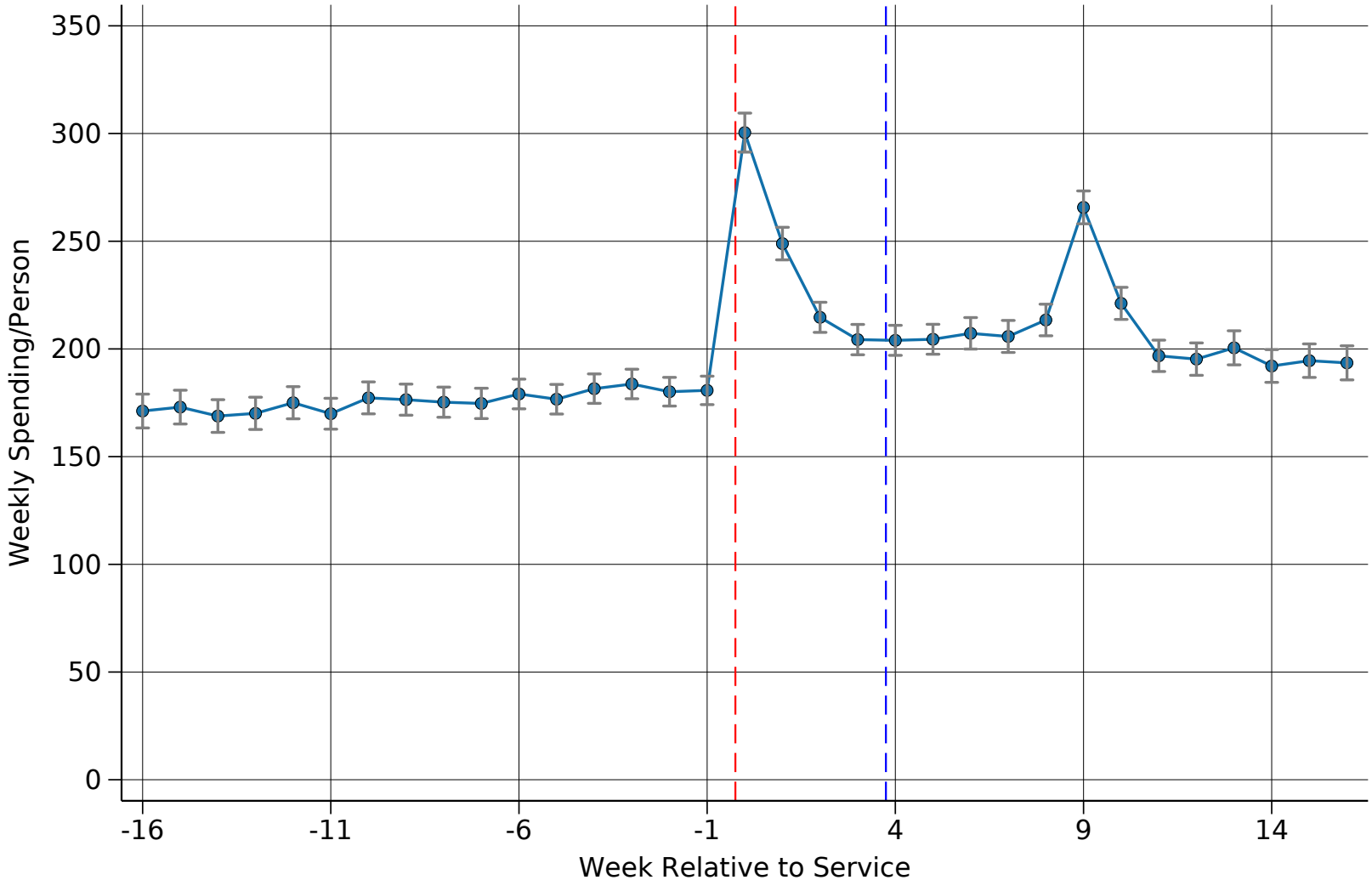
11:55 AM · Oct 7, 2022 · Twitter Web App

How responsive are consumers *before* prices are known?

Scenario 1: Payer information (EOB) arrives in same week as service



Scenario 2: EOB arrives a month *after* service



Setting & Research Questions

Setting: Household responses to "Shoppable Health Services"

- Examples: Biopsies/colonoscopies, arthroscopy, cataract removals
- Average [median] OOP costs around $650 [$200]
- Examine **spillover responses** in future health consumption

Setting & Research Questions

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Our Questions:

1. **How responsive are consumers before prices are known?**
   - Does information about the *true cost* of service change responses?
2. **What information is contained in a bill?**
   - Which households respond to the bill?
   - Is there evidence of response to *price information*?
   - What services are affected?
3. **What information do patients internalize prior to receiving a bill?**
   - Model of **imperfect moral hazard** with *delayed learning*
   - How do mis-perceptions of OOP spending influence over-consumption of care?

Preview of Results

1. Household consumption $\uparrow\uparrow$ following service but $\downarrow$ when bill arrives
   - Estimated bill effect is ~**20%** of total spending increase

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   - Patients with lower initial spending have larger “swings" in spending
   - Bill effects are strongest for bills that *almost* met deductible
   - Bill effects are largest for highly elastic services
     (preventable hospitalizations, E&M, labs)

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3. Households **over-estimate** OOP spending before bills:
   - Model suggests households inflate spending by ≈ 10%
   - 1 in 10 over-consume care: $842.80 [$480.59] *per household member*
   - Evidence of learning but with **very misinformed** priors

OUTLINE

1. Setting & Data: CMS Shoppable Services
2. Empirical Results: Effect of Bills on Spillover Responses
3. Heterogeneity: Evidence of Partial Price Information
4. Model: Imperfect Moral Hazard in Health Care
5. Counterfactual Simulations: Policy Relevance & Conclusions

SETTING & DATA

Setting: Shoppable Health Services

- Household responses to planned + nontrivial health expenditures
- 30 CMS **"shoppable services"**: non-urgent scheduled services

Type	Code	Service Description
CPT	19120	Removal of 1 or more breast growth, open procedure
CPT	29881	Removal of one knee cartilage using an endoscope
CPT	42820	Removal of tonsils and adenoid glands (patient younger than age 12)
CPT	43239	Biopsy of the esophagus, stomach, and/or upper small bowel
CPT	47562	Removal of gallbladder using an endoscope
CPT	49505	Repair of groin hernia (patient age 5 years or older)
CPT	55700	Biopsy of prostate gland
CPT	55866	Surgical removal of prostate and surrounding lymph nodes
CPT	59400	Routine obstetric care for vaginal delivery
CPT	59510	Routine obstetric care for cesarean delivery
CPT	59610	Routine obstetric care for vaginal delivery after prior cesarean delivery

Data

Data: Truven Commercial Claims and Encounters Marketscan, 2006–2018

- Detailed claims for households in private group plans
- **Large sample:** 8 firms, N = 386,240 families
- Data provides **deep dive** into utilization and spending

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Exogenous Variation: Waiting times for bills

- Comparison group: households who haven't had services yet (Fadlon & Nielson, 2019)
- Wait times for bills are exogenous at the household level
- Divides response into 2 periods: "interim" and post-bill

Summary Statistics Waiting Times for Bills

EMPIRICAL EVIDENCE

Methods: Triple-differences Poisson Regression

We use a **triple-differences** framework to identify the **causal effect of a bill's arrival** on household spending choices:

$$\mathbb{E}[\text{spend}_{ity}] = \exp\left\{\beta_1 \mathbb{1}(\text{post\_service}_{ity}) + \beta_2 \mathbb{1}(\text{post\_bill}_{ity}) + \text{FEs}\right\}$$

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- Poisson regression: multiplicative effects on spending
  - For skewed (nonnegative) spending data + weeks with 0 spending
  - Assumption for consistency: conditional mean $\mathbb{E}[\text{spend}_{ity}]$ is correctly specified (same as OLS)
- Triple-differences separates periods by plan paid date
- Individual, week-of-year, year, and MD fixed-effects
- β_2 is causal to the extent that bill timing is random

Balance in Bills

A Bill's Arrival Dampens Household Spending Responses

	Main Models		Alternative Specifications		
Post Service	0.402***	0.464***	0.597***	0.472***	0.486***
	(0.0022)	(0.0032)	(0.0032)	(0.0032)	(0.0033)
Post Bill		-0.077***	-0.080***	-0.096***	-0.076***
		(0.0030)	(0.0030)	(0.0030)	(0.0031)
$\overline{\text{spend}}_{it}$	$120.49	$120.49	$120.49	$120.49	$120.49
Household FEs	X	X	X	X	X
Year FEs	X	X		X	X
Week of Year FEs	X	X			X
Provider FEs	X	X			
Observations	61,860,735	61,860,735	61,860,735	61,860,735	61,860,735

- Bill effects are **consistently estimated**
- Constitutes $\approx$ **1/5 of total household response**!
- Robust to placebo wait times Placebo Tests

WHO LEARNS WHAT FROM BILLS?

Who Learns What From Bills?

Bills may drive spending decisions due to different types of **information**:

- **Pricing**: households learn about service (OOP) prices
- Coverage: households learn that procedures are/aren't covered
- Billing Practices: billing mismatches between patients and providers

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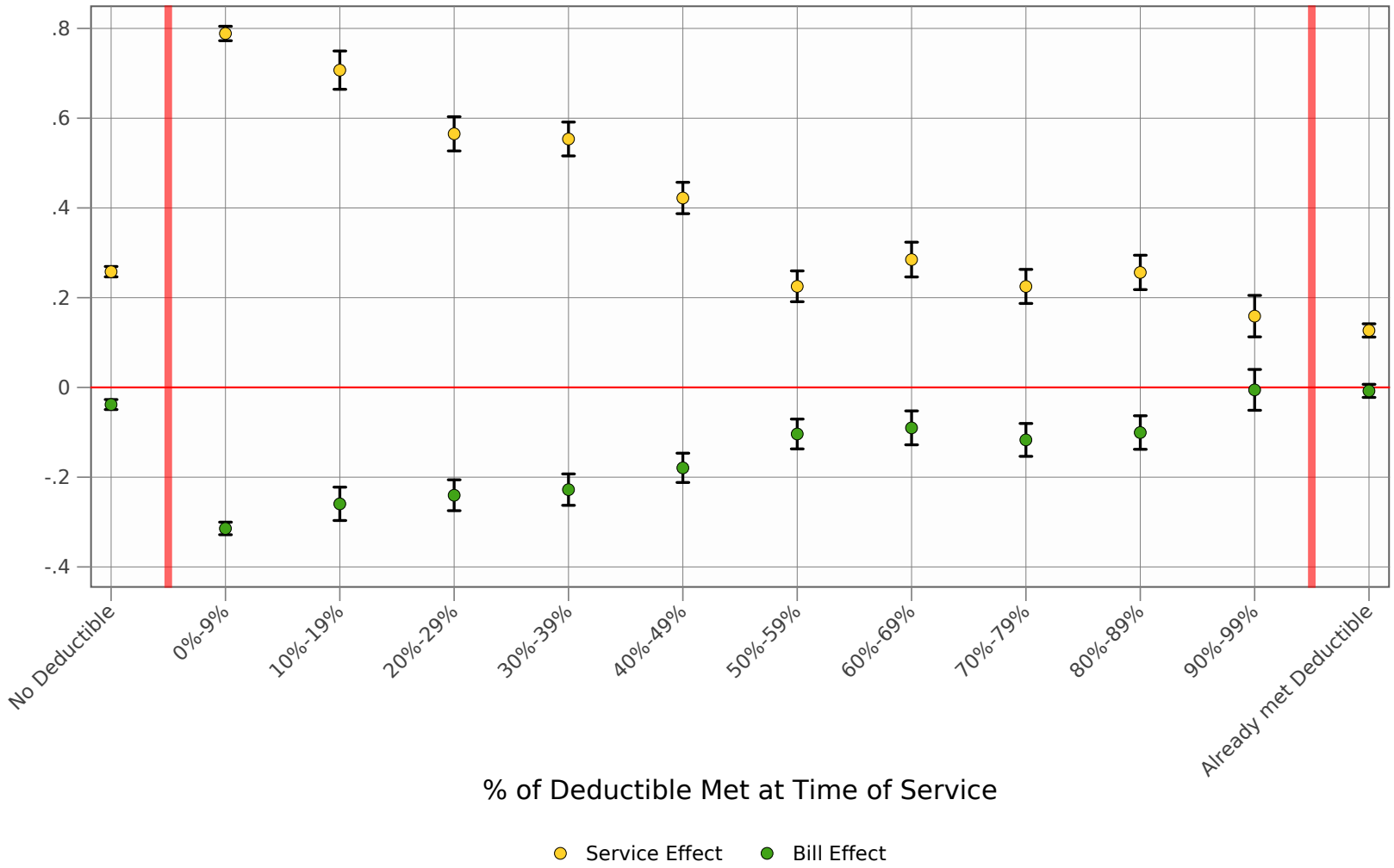
Understanding mechanisms of bills

1. What types of households respond to bills?
2. What types of expenditures are particularly salient?
3. What types of services are affected?

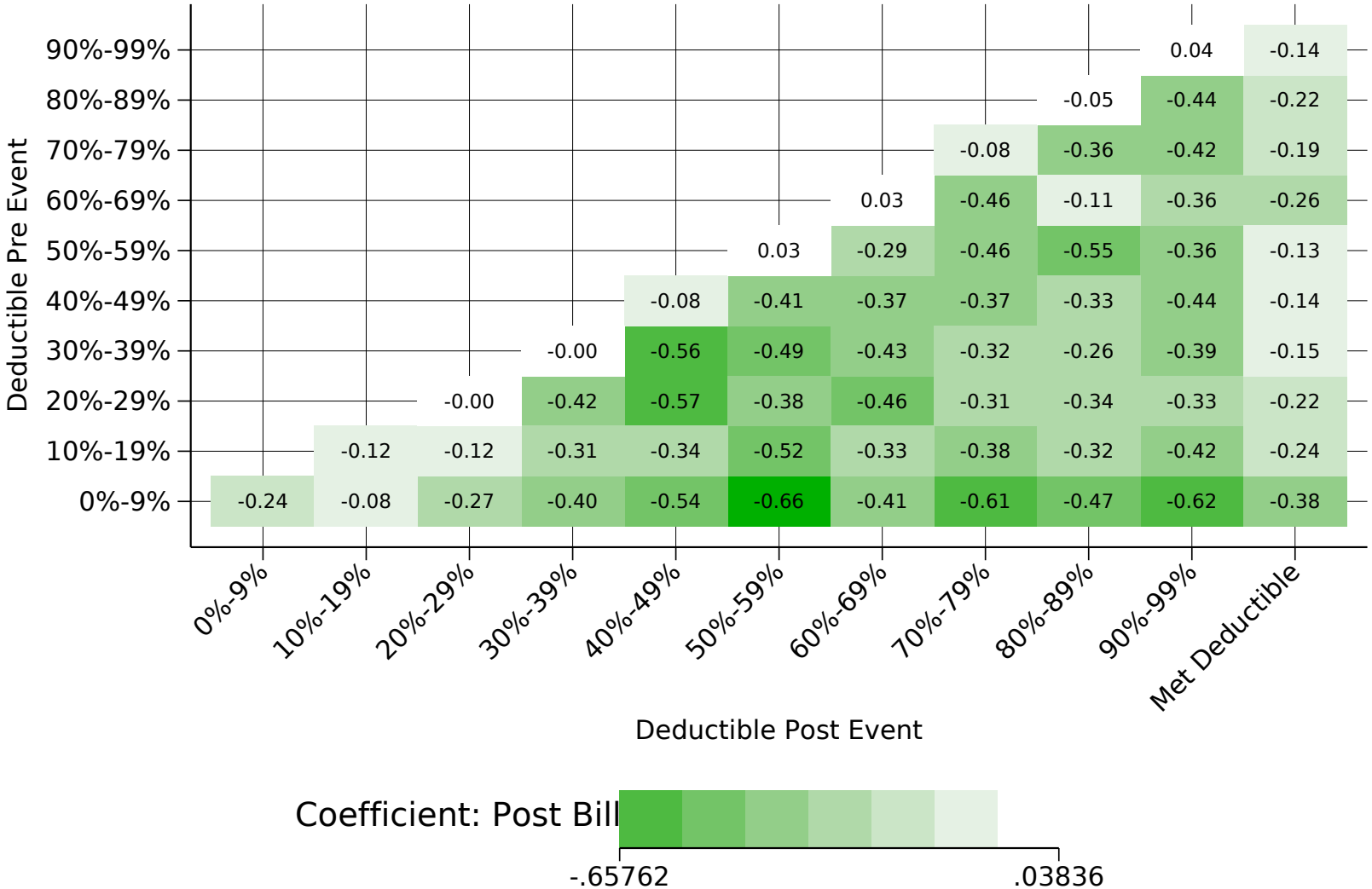
Note: from here on, only use data through 2013 due to plan identifying information.

Who Responds? Households with Lower Pre-Event Spending



- Responses are largest for **low-spending households** Combined
- Responses converge to 0 for high-spending households

Expenses “Landing" You Close to Deductible Are Most Salient



- Responses are (still) largest for **low-spending households**
- Responses are most salient for bills *just shy* of deductible

MODEL

Model Primitives

Individuals choose weekly **health spending** m_{it}^* in response to:

- Individual health shock λ_{it}
- Individual moral hazard parameter ω_i
- Household spending $c_{ij}\left(\sum_{i \in \mathcal{I}} m_{it}\right)$

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What about delays in medical bills? (When $M_{\mathcal{I}t}$ isn't known)

1. Spending is **estimated** as θ before bill arrives:

$$\theta = \underbrace{\sum_{s=0}^{t-\tau}\sum_{i\in\mathcal{I}} c_{ij}(m_{is})}_{\text{known spending}} + \underbrace{\sum_{s=t-\tau+1}^{t}\sum_{i\in\mathcal{I}} s_i(m_{is}|x_{is})}_{\tilde{\theta}=\text{unknown spending}}$$

   - Each spending event is a signal that takes time to be processed

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2. **Main question**: how do households perceive $M_{\mathcal{I}t}$ before signals?

Simple Case: Constant Discounting by β

Suppose that: each signal $s_i(m_{is}|x_{is}) = \beta c_{ij}(m_{is})$

In this case, θ can be simplified:

$$\theta = \sum_{i \in \mathcal{I}} \sum_{s=0}^{t} (1 - D_{is}) \beta c_{ij}(m_{is}) + D_{is} c_{ij}(m_{is}),$$

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What value of β matches observed data?

Optimal spending choice in each period is given by:

$$m_{it}^{*} = \max\{0, \lambda_{it} + \omega_i(1 - \hat{c}_{it})\}$$

- Parameterization of $(u(\cdot), \lambda, \omega)$ allows identification of β
  - ω_i: calibrated from Einav et al. (demographics + risk scores)
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Identification & Learning

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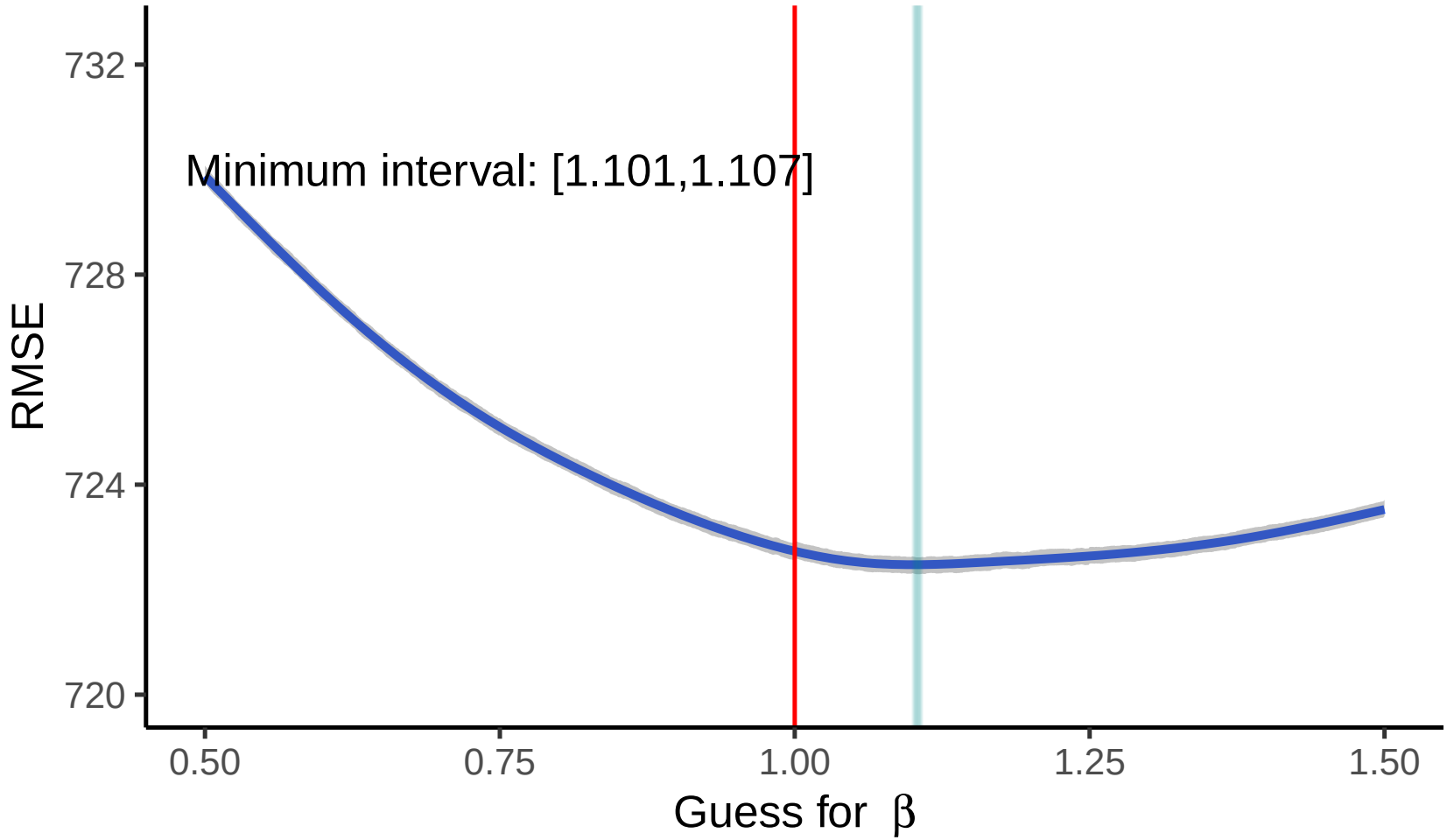
We can also incorporate simple **Bayesian learning** about β:

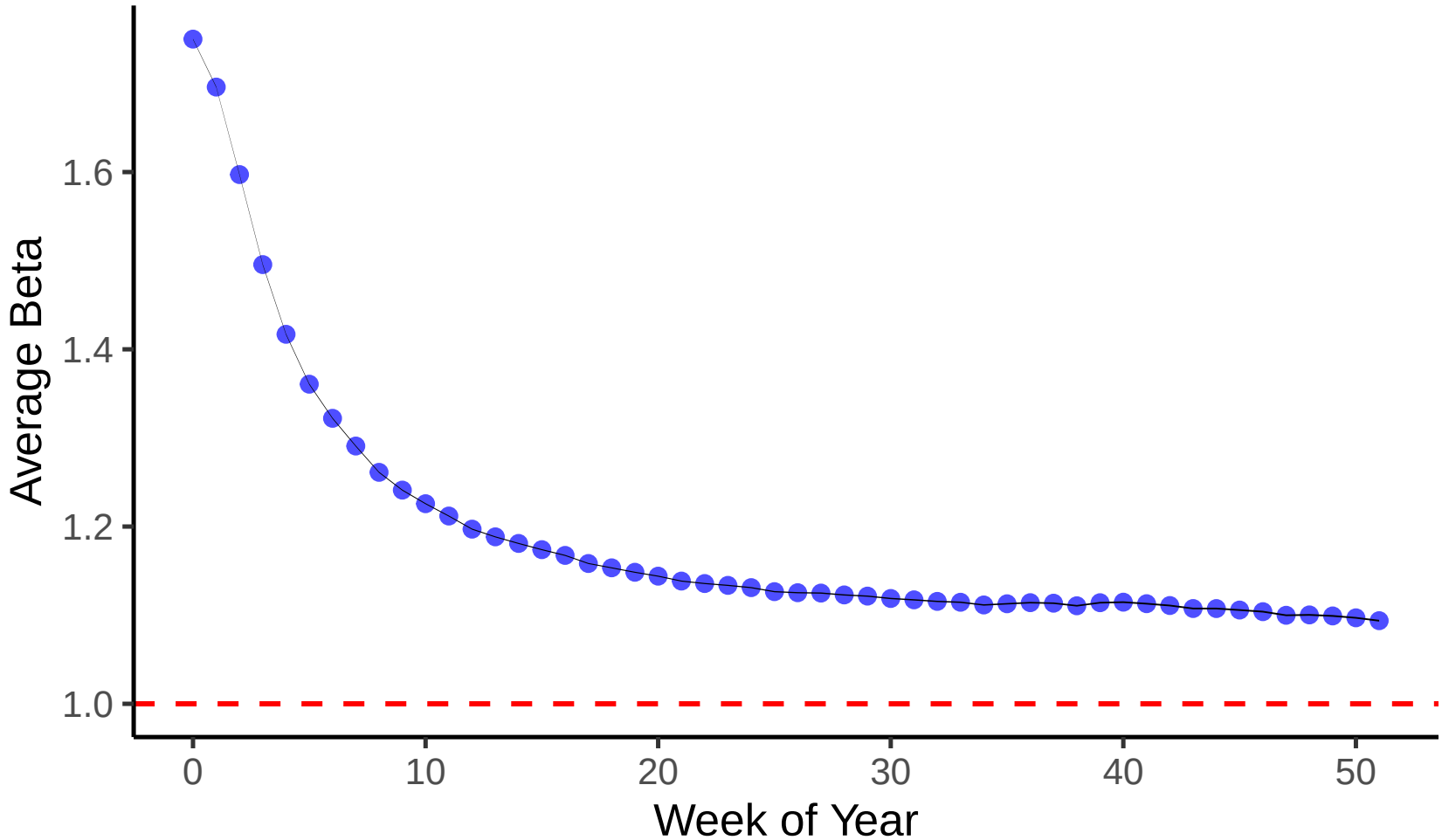
1. Households have prior beliefs $\beta_{i0} \sim \mathcal{N}(\mu_0, \sigma_0^2)$
2. Each medical encounter is a signal $s_{it} \sim \mathcal{N}(1, s^2)$
3. Each parameter in (μ_0, σ_0^2, s^2) identified by within- and across-household variation in spending + bill times

Model Results: No Learning



- Households spend as though $\beta \approx 1.1$
- Leads to over-consumption for 10% of households of $842.80

Model Results: Learning



- Estimated parameters are $(\mu_0, \sigma_0^2, s^2) \approx (1.8, .026, .001)$
- Medical encounters are informative for those who have enough

Counterfactual Simulations

- Incorrect info $\Longrightarrow$ over-consumption across periods & people
- Tradeoffs in shortening deductibles: $\uparrow$ instances of $\downarrow$ uncertainty

DISCUSSION & CONCLUSIONS

Conclusions

Our analysis highlights:

1. Households are under-informed about prices before a bill arrives
2. Bills cause households to “reign in" spending responses
3. Collective evidence suggests households over-inflate OOP spending
4. Leads to over-consumption of care + potential for cascades of care

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Future work:

- Counterfactual simulations of alternative plan designs
- Actual data on physician billing practices / patient interactions
- Equity concerns of under-information
- impact of real-times claim adjudication on consumer spending responses

WHAT'S IN A BILL?

A MODEL OF IMPERFECT MORAL HAZARD IN HEALTHCARE

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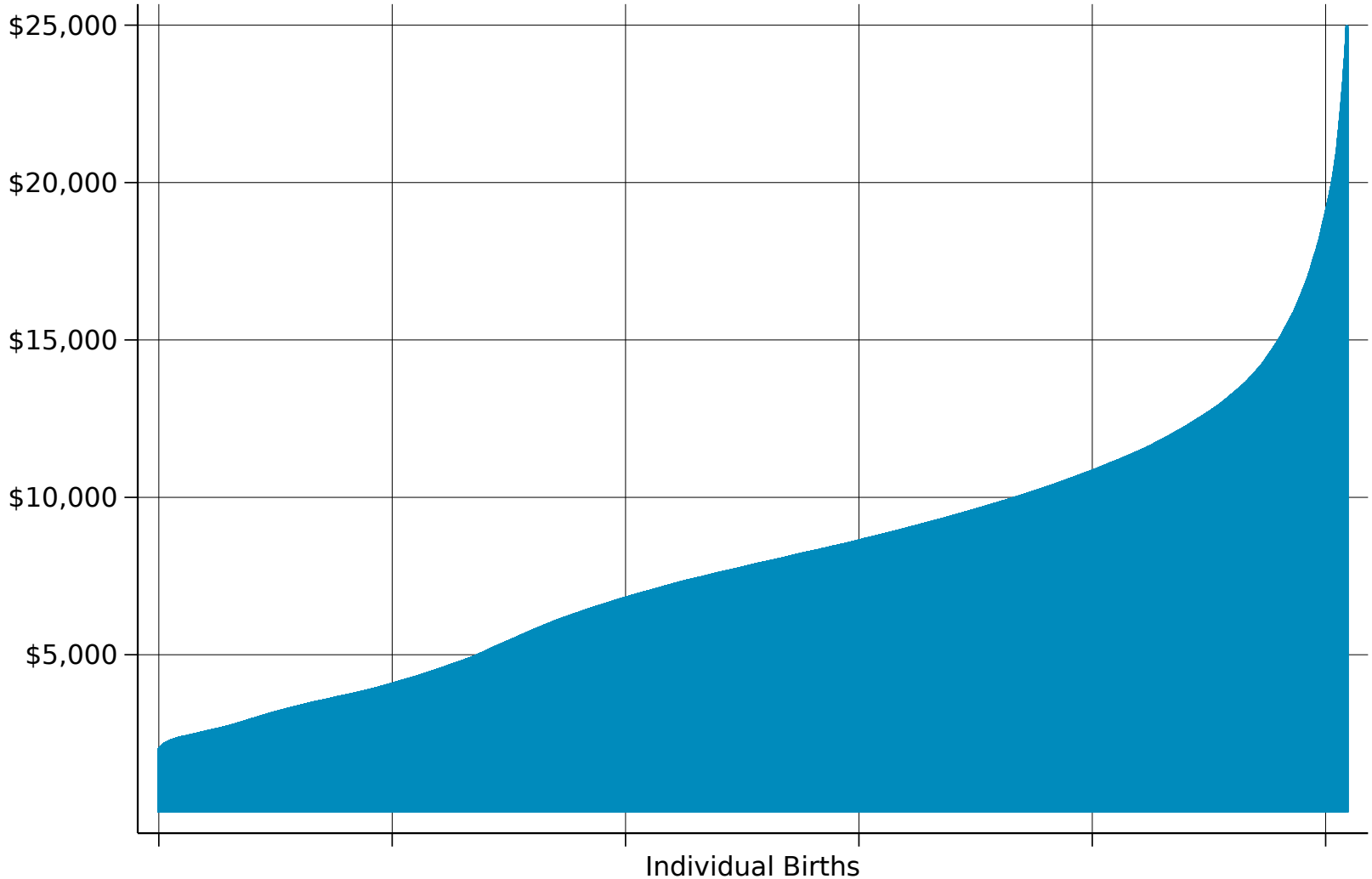
APPENDIX

References

- Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013). Selection on moral hazard in health insurance. *American Economic Review*.
- Fadlon and Nielson (2019). Family health behaviors. *American Economic Review*.

Motivation: Variation in Service Prices



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Summary Statistics

	Full Sample	Plan-Identified Sample
Total spending	$4,764 [$975] (0.002)	$4,406 [$887] (0.002)
% with 0 spending	0.17 (0.000)	0.20 (0.000)
OOP spending	$650 [$198] (0.000)	$562 [$167] (0.000)
Deductible | > 0	—	$1,040.24 (0.001)
% with 0 deductible	—	0.26 (0.000)
% w/ shoppable services	0.06 (0.000)	0.06 (0.000)
Total cost	$5,572 [$3,721] (0.011)	$5,645 [$3,814] (0.015)
OOP	$691 [$388] (0.002)	$574 [$290] (0.002)
Years	2006–2018	2006–2013
N_{families}	368,237	367,445
$N_{\text{individuals}}$	1,357,392	1,311,554

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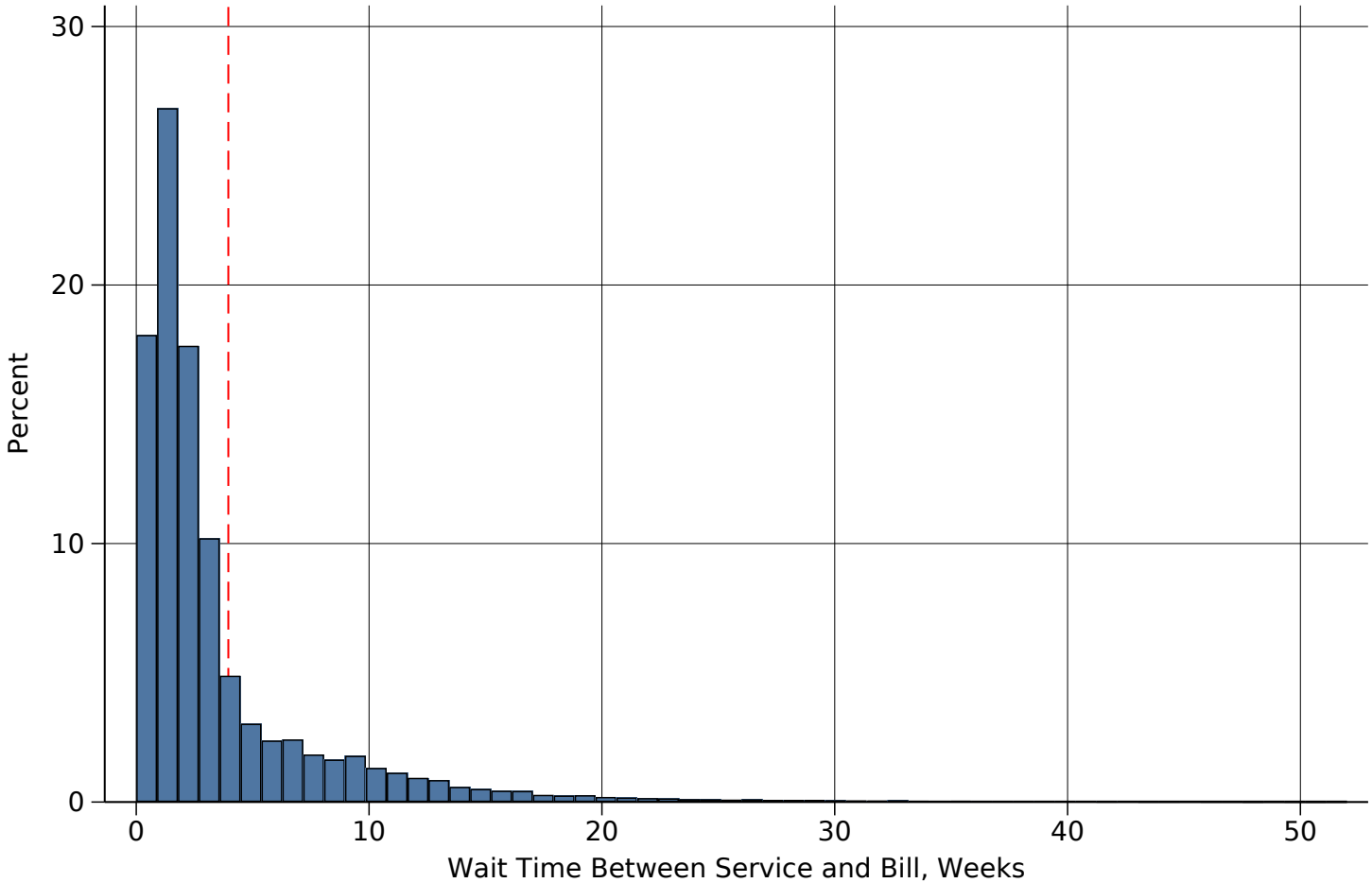
Variation in Waiting Times for Bills

Substantial (quasi-random) variation in waiting times for bills



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Bill Balance Table

Procedure	Average Spending $d \leq 30$	Average Spending $d > 30$	Difference Unadjusted	Difference Adjusted	p-value	Sample Size $d \leq 30$	Sample Size $d > 30$
Removal, prostate	\$21,834	\$25,362	\$3,528	\$1,260	0.41	917	403
Removal, knee cartilage	\$7,619	\$8,021	\$402	\$697	0.00	46,937	15,606
Removal, breast growth	\$4,887	\$5,173	\$286	\$674	0.00	10,550	3,916
Injection, anesthetic	\$3,258	\$3,537	\$279	\$484	0.00	49,604	16,667
Biopsy, esophagus/stomach	\$3,317	\$3,238	-\$79	\$406	0.00	245,411	65,603
Removal, tonsils (age < 12)	\$4,578	\$4,871	\$293	\$342	0.00	21,503	4,962
Shaving, shoulder bone	\$12,262	\$12,040	-\$222	\$233	0.07	27,952	11,410
Biopsy, prostate	\$2,653	\$2,377	-\$276	\$124	0.01	23,172	6397
Removal, gallbladder	\$9,217	\$9,794	\$577	\$96	0.38	36,756	13,252
Hernia repair	\$6,753	\$6,724	-\$28	\$28	0.83	14,314	5,215
Removal, cataract (no insertion)	\$1,408	\$1,198	-\$210	-\$179	0.05	11,776	2,388
Vaginal delivery	\$7,789	\$7,927	\$139	-\$344	0.00	82,968	36,068
Removal, cataract (lens insertion)	\$6,114	\$5,958	-\$156	-\$346	0.00	43,129	9,266
Vaginal delivery, prior C-section	\$8,429	\$8,634	\$205	-\$912	0.01	1298	503

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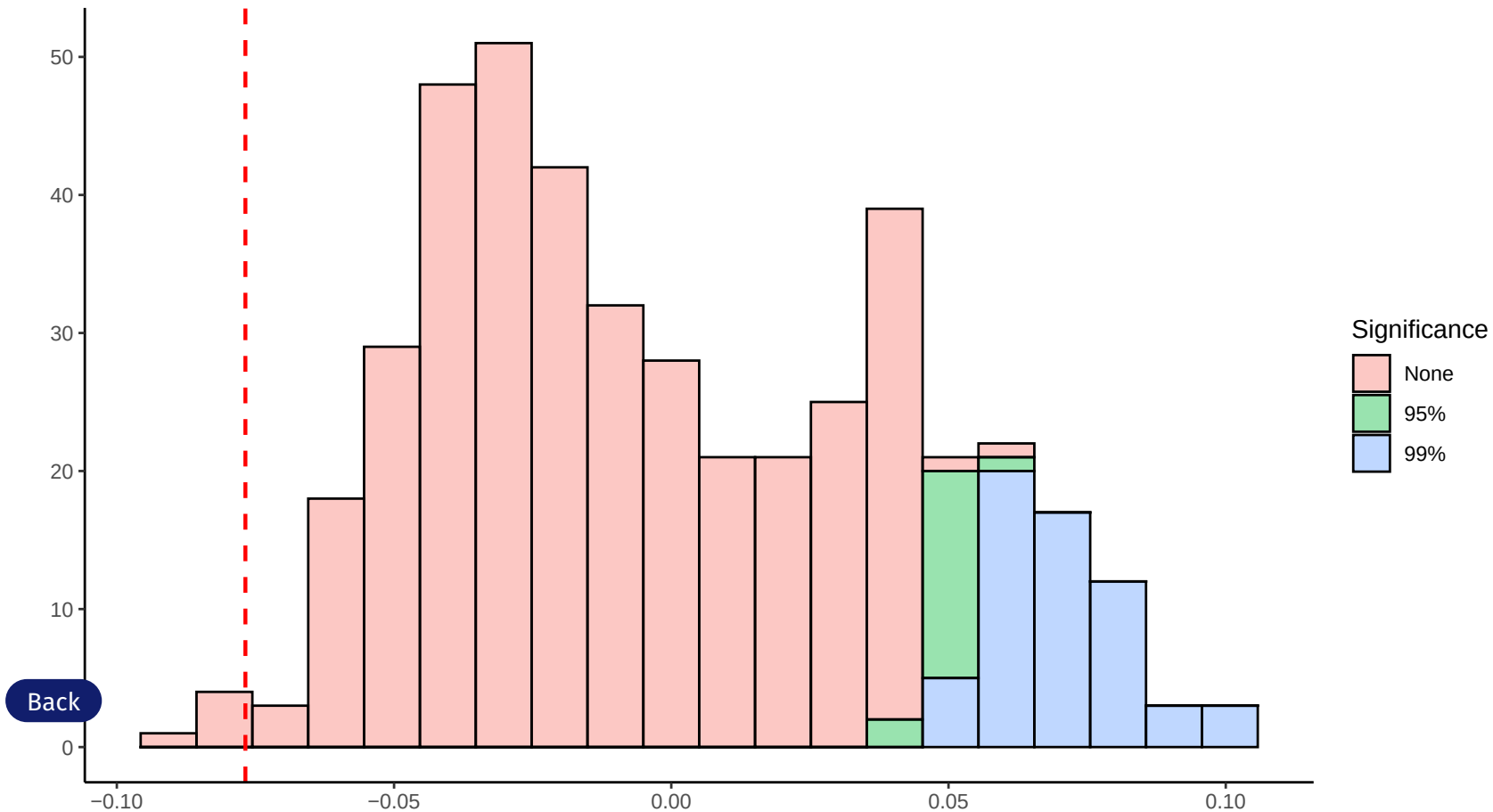
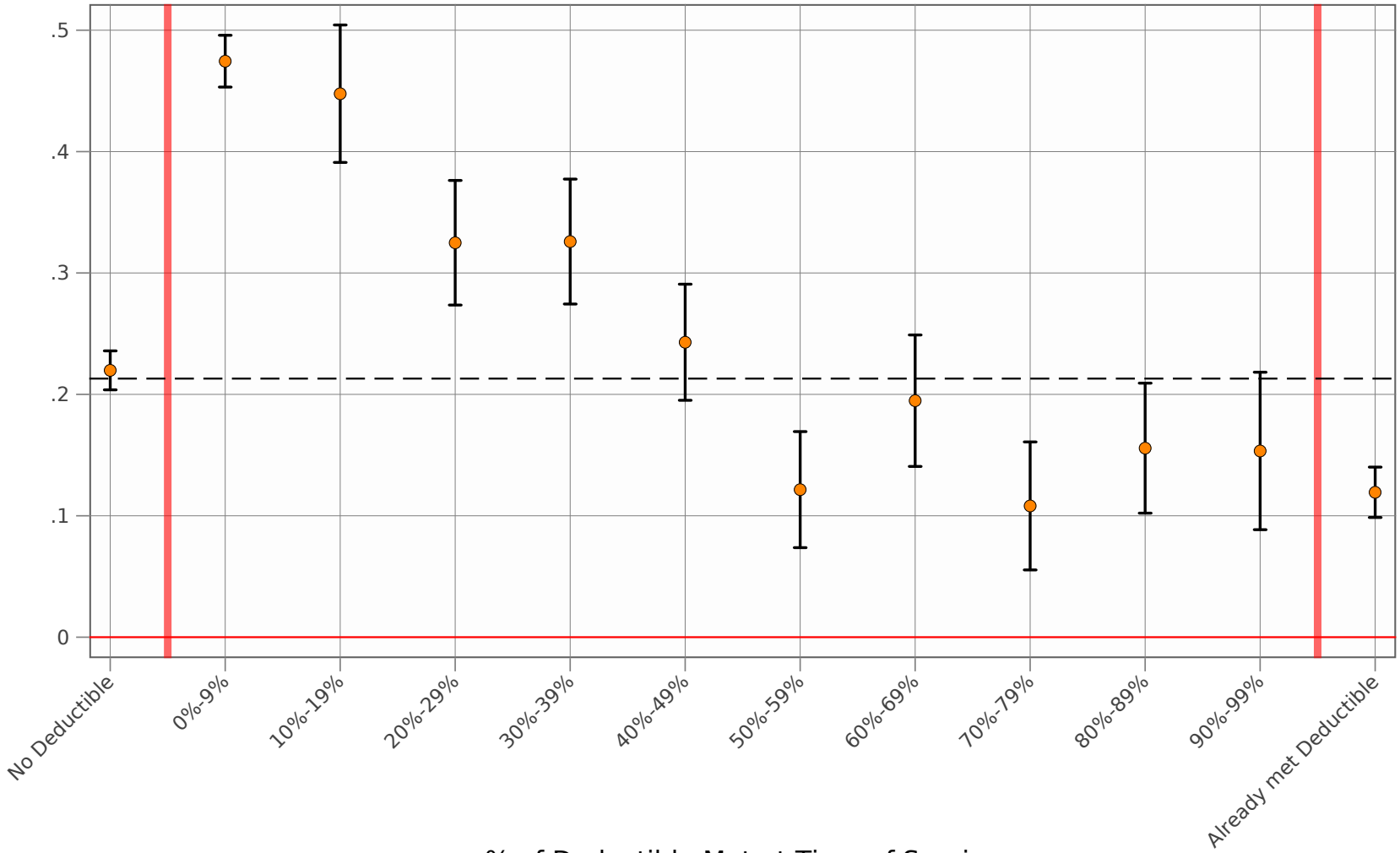
Placebo Tests: Is the Timing Just Random?

We conduct placebo tests to assess if results are driven by timing of household responses:



Regression Results by Deductible Fraction



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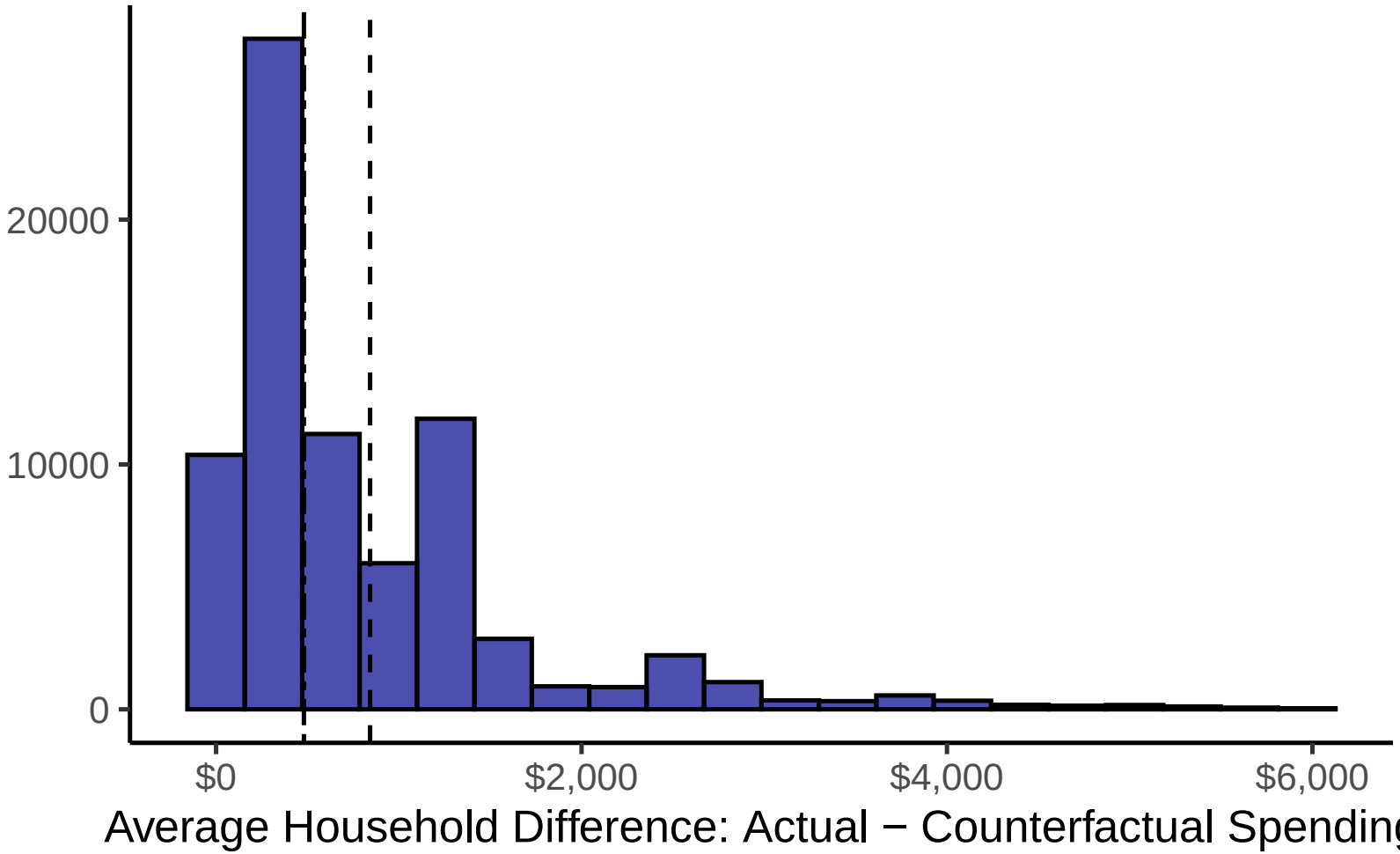
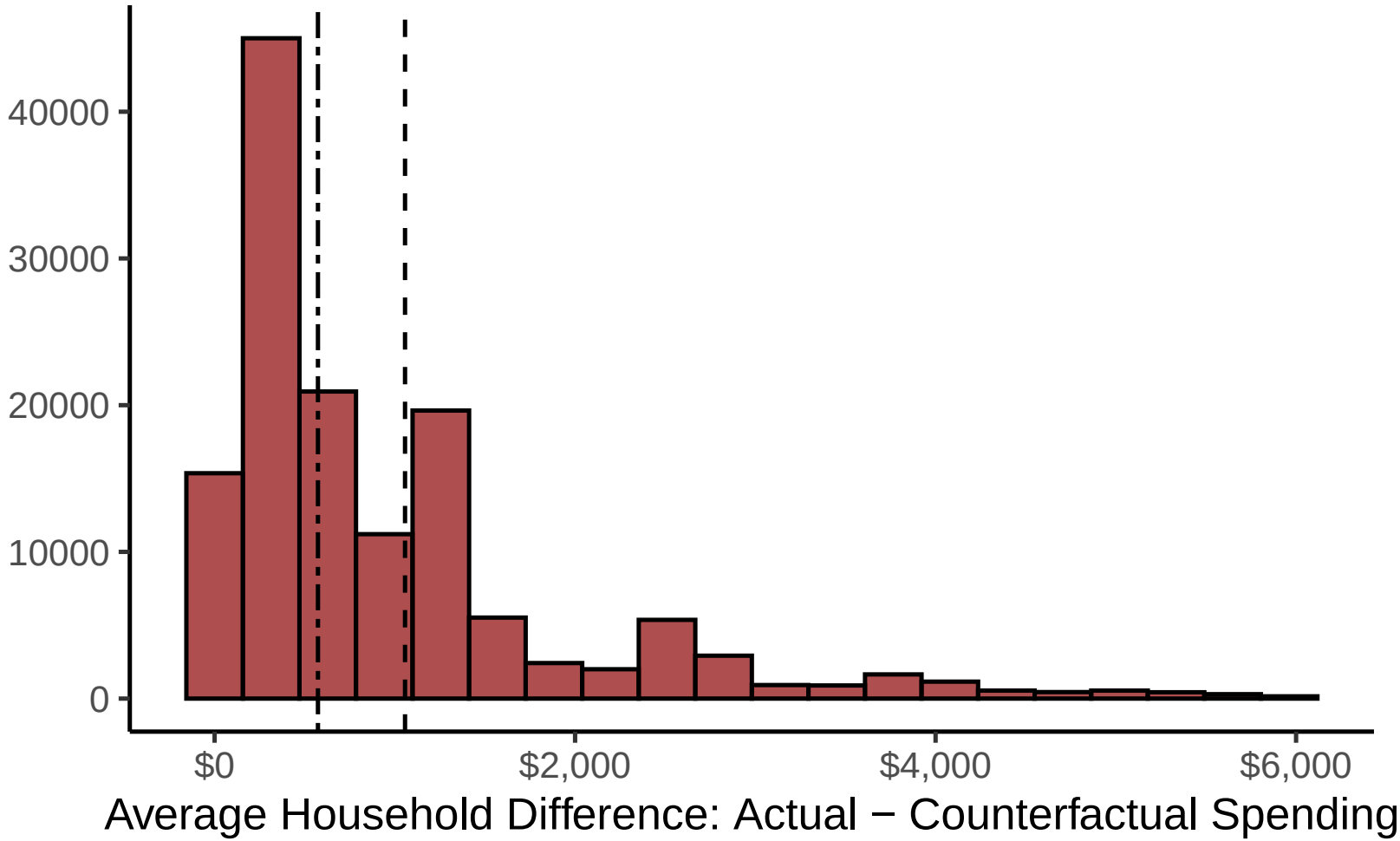
Counterfactual Model Results: No Learning



Counterfactual Model Results: Learning



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