Information and Disparities in Health Care Quality: Evidence from GP Choice in England

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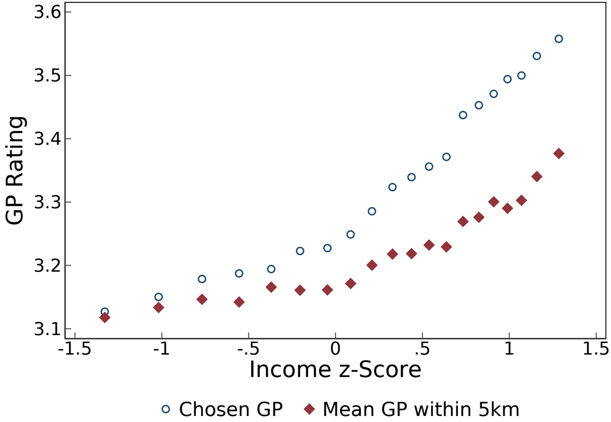
Does Access to Information Drive Disparities in Health Care Quality?

- Low-income individuals receive lower quality care (e.g., Hart, 1971; Scobie and Morris, 2020)
  - Even in high income countries with free public health care (e.g. the UK)
- Why?
  - Information barriers about provider quality?
  - Differences in preferences or access?
  - Difficult to separate information, preferences and access
- Understanding the role of information key for determining:
  - Best way to address disparities (information interventions vs. other means)
  - The value of increasing choice in public services (e.g. Gaynor et al. 2016)

Disparities in General Practitioner (GP) Choice in the English NHS



- Strong correlation between income and multiple quality measures of chosen GP, despite zero cost to patients
    - Only partially driven by differential access

This Paper: Exploit Star Rating Website

1. Reduced form: do public star ratings (differentially) impact GP enrollment?
    - Regression discontinuity **(RD)** approach based on rounding of average reviews
    - Test for information gaps using differences in impact between high and low income
2. Structural model of GP Choice: quantify role of information disparities
    - Patients learn about quality and update their beliefs before choosing a provider
    - Estimated by indirect inference incorporating RD moments
    - Allow for inertia + heterogeneity in information precision/preferences
    - Counterfactuals identify the role of information, access and preferences in the health-income gradient

Outline

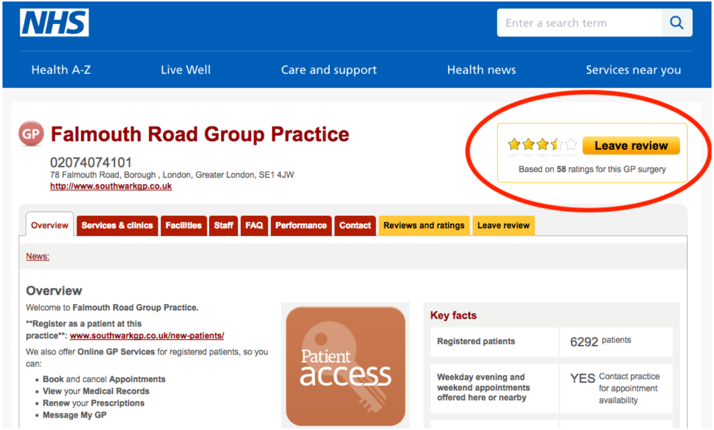
Background and Data

Regression Discontinuity Effect of Star Ratings

Empirical Model

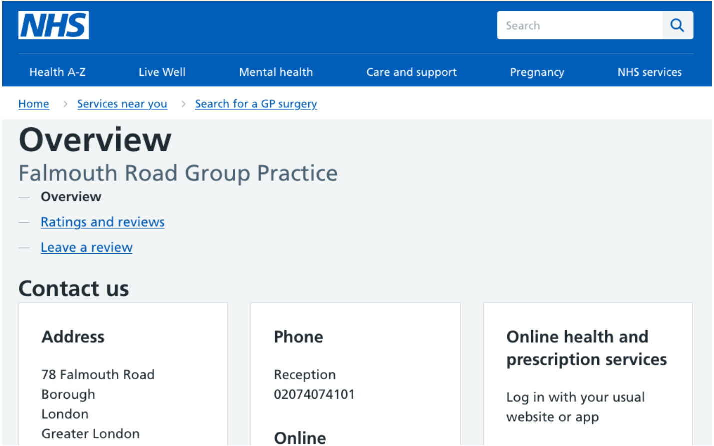
Conclusion

NHS Website with Visible Star Rating (before January 2020)



- Star rating based on rounded 2-year moving-average of reviews
- NHS took a number steps to ensure credibility of reviews

NHS Website with No Star Rating (after January 2020)



- Star rating removed in January 2020
- We will use this period for a falsification test

Data

- Reviews for all GPs in England
  - ≈400,000 individual reviews for 2013–2022
  - Construct panel of average reviews by GP-quarter (2 year moving average)
  - Reviews are highly correlated with representative patient surveys and objective measures of clinical quality (Greaves et al. 2012)
- GP enrollment for all individuals in England
  - At GP-quarter-neighborhood level for 2015–2022
  - Merge with income, education, health, and employment by neighborhood
  - Use geolocation of GPs to get distance to each patient
  - Individual-level sample of movers to new neighborhoods (must choose new GP)

Background and Data

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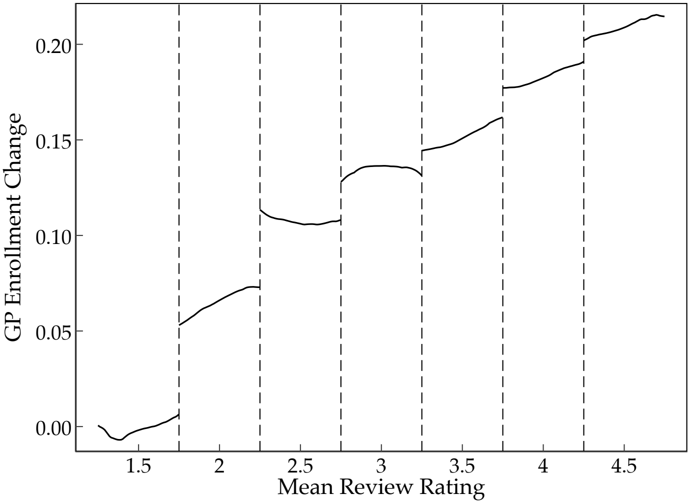
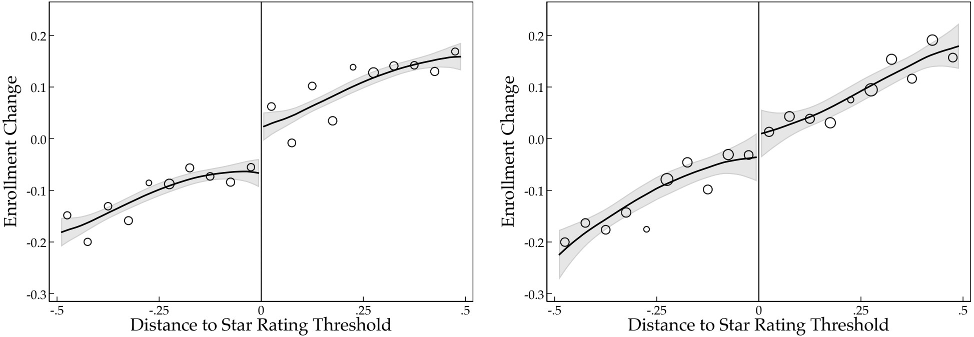
Testing for the Impact of Star Ratings on Demand

- RD recovers the impact of star ratings on enrollment
  - Two GPs may have different star ratings with similar mean reviews (e.g., Luca 2016)
  - Main outcome: quarterly change in enrollment
- Response at the thresholds identifies patient information about GP quality
  - Perfect baseline information $\Rightarrow$ no response to star ratings
  - Baseline uninformed patients $\Rightarrow$ sharp response to ratings

GP Enrollment Change and Review Thresholds



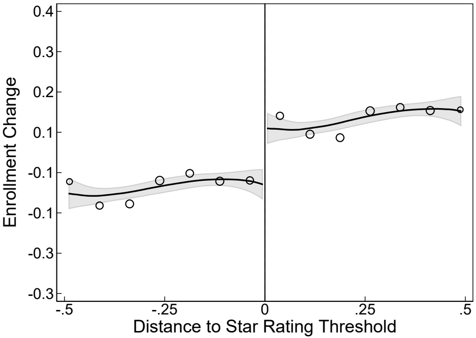
Patients Learn from Star Ratings: Positive Effects on GP Enrollment



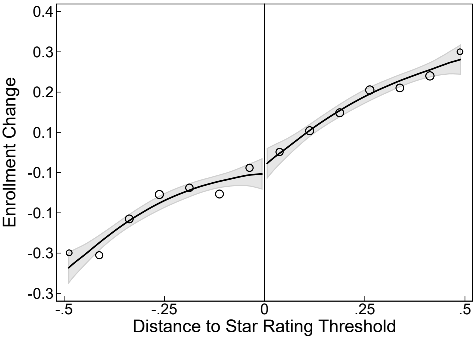
a. **Visible Star Rating** b. **No Star Rating (post Jan 2020)**

- Significant effect at star ratings threshold (no effect once stars removed)

Evidence of information gap between low and high income patients



a. **Low Income**



b. **High Income**

- Large jump for low-income ⇒ rely heavily on star ratings
- Steep slope + no jump for high income ⇒ already informed

Regression Discontinuity by Income

	Visible Star Ratings		No Star Ratings	
	Low Income	High Income	Low Income	High Income
Estimate	0.185***	0.058	−0.098	0.153
	(0.068)	(0.072)	(0.140)	(0.139)
Robust CI	[.05 ; .359]	[-.1 ; .238]	[-.479 ; .179]	[-.133 ; .524]
Bandwidth	0.15	0.12	0.11	0.12
N	507,107	427,664	138,215	140,707
Test for Diff. by Inc.		2.64		-1.44

- Implement bandwidth selection procedure and SEs following Calonico et al. (2014) and Cattaneo et al. (2020)
    - Significant effect for low-income but no statistically significant effect for high-income
    - One half star higher rating increases enrollment growth by $\approx$ 20% of the mean

RD Results

- No evidence of endogenous sorting across the threshold
  - Density test t-stat: 1.15
- Similar effect for movers who much choose GP
  - Addresses concern about differential switching
  - Effect still almost entirely driven by low-income
- Results robust to panel FE strategy (variation: within-GP rating changes)

Empirical Model of GP Demand with Learning About Quality

- RD indicates presence of an information gap by income...
  - But cannot quantify relative importance of access, information, & preferences
- Empirical model
  - Leverage RD to separately identify preference vs. information heterogeneity
  - Account for heterogeneous inertia in provider choice
  - Counterfactuals decompose sources of disparities in health care quality in long run

Learning about GP Quality

- Star ratings s_j are public and all individuals have prior

$$r_j | s_j \sim N(\mathbb{E}[r_j | s_j], \sigma_s^2)$$

where $\mathbb{E}[r_j | s_j]$ is expected quality given rounded star rating s_j

- Individual i receives private signal (word-of-mouth, Google Maps, etc)

$$\tilde{r}_{ij} = r_j + \varepsilon_{ij}$$

where $\varepsilon_{ij} \sim N(0, \sigma_i^2)$ and σ_i^2 characterizes the precision of i's information

- Bayesian updating gives posterior

$$\mathbb{E}[r_j | \tilde{r}_{ij}, s_j] = \alpha_i (r_j + \varepsilon) + (1 - \alpha_i) \mathbb{E}[r_j | s_j], \quad \text{where} \quad \alpha_i = \frac{\sigma_s^2}{\sigma_i^2 + \sigma_s^2}.$$

Empirical Model

- For individual i in neighborhood ℓ, expected utility for choosing GP $j \in \mathcal{J}_{\ell t}$ is:

$$\mathbb{E}[u_{i\ell jt}] = \beta_{1\ell}\left[\alpha_\ell r_j + (1-\alpha_\ell)\mathbb{E}[r_j | s_{jt}]\right] + f(d_{\ell j}, X^d_{\ell t}; \beta_2) + \beta_3 X_{jt} + \xi_j + \nu_{i\ell jt}$$

  - Preference for quality, $\beta_{1\ell}$, is function of income
  - Weight on private signal, α_ℓ, depends on precision σ^2_ℓ (will be a function of income)
  - $f(d_{\ell j}, X^d_{\ell t}; \beta_2)$ is disutility from distance, depends on characteristics $X^d_{\ell t}$
  - X_{jt} is a vector of time varying GP characteristics (GP experience, capacity)
  - ξ_j is a fixed effect for GP j (unobserved amenities)
  - $\nu_{i\ell jt}$ is EV1 error capturing both error in beliefs and taste shock

- Individuals re-optimize with probability θ (function of income/age/health), otherwise stay in their current GP

Indirect Inference Estimation

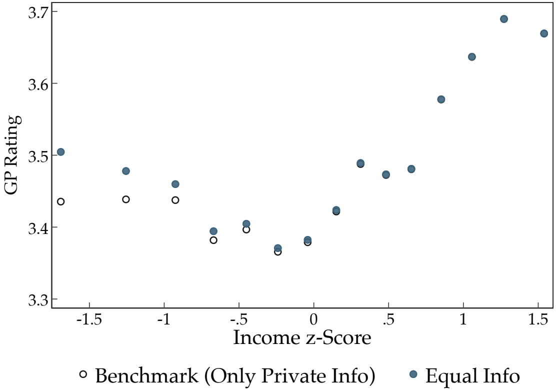
- Target four sets of moments
  - RD estimates
  - Market shares
  - Average characteristics
  - Switching rates
- For computational tractability, estimation sample is Greater London (pop 10M)

Demand Estimates

	Estimate	SE
Inertia (θ)		
Constant	-3.406	(0.002)
Income	0.095	(0.002)
Private Signal Precision ($\frac{1}{\sigma_\ell^2}$)		
Constant	4.313	(0.572)
Income	2.214	(0.617)
GP Quality ($\beta_{1\ell}$)		
Constant	0.284	(0.020)
Income	0.011	(0.021)
Distance ($\beta_{2\ell}$)		
Constant	-1.778	(0.028)
Income	0.036	(0.029)
Other GP Characteristics (β_3)		
Mean physician age	0.049	(0.026)
Practitioners per 1000 Patients	0.224	(0.046)
Active choice fraction	0.032	

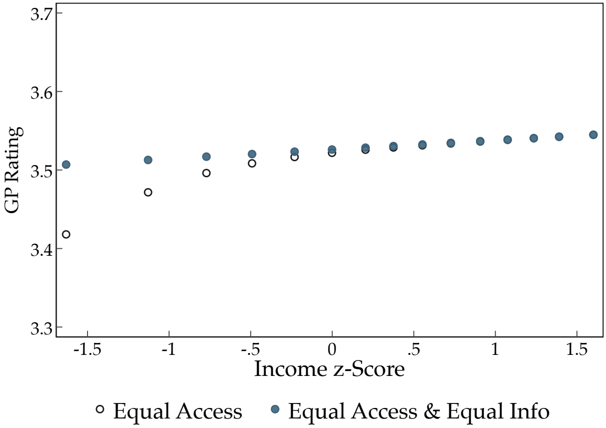
- Large degree of inertia
- High income individuals more informed
  - Precision is increasing in income
- High income less sensitive to distance
- High income slightly more sensitive to quality
- Preference for less crowded GPs

Counterfactual 1: Equate information



- If low income individuals had same info as high income, correlation between income and ratings would be 24% lower relative to status quo (without star ratings)

Counterfactual: Equate Access and Information



- If quality was uniformly distributed, this would also reduce disparities
- Equalizing both access and information eliminates almost 90% of inequality

Counterfactual Summary

Counterfactual	Income-Quality Correlation	Percent Change Relative to No Stars
Benchmark	0.091	
Equal Information	0.069	-24%
Equal Access	0.040	-55%
Equal Information + Equal Access	0.013	-86%
Stars	0.070	-22%
Stars + Equal Access	0.014	-85%

- Information and access are complements
  - High quality options are more valuable if individuals know about then
- Stars help reduce inequality but are not as effective as full information
- Counterfactuals are largely robust to allowing capacity to endogenously adjust

Conclusion

- High income individuals are more likely to choose high quality providers
- Information differences play a meaningful role in driving disparities
  - 2020 removal of star ratings primarily hurt low-income individuals
- Reducing health care inequality requires both access and information
- Welfare effects of increasing choice depend on who has information

Thank you!

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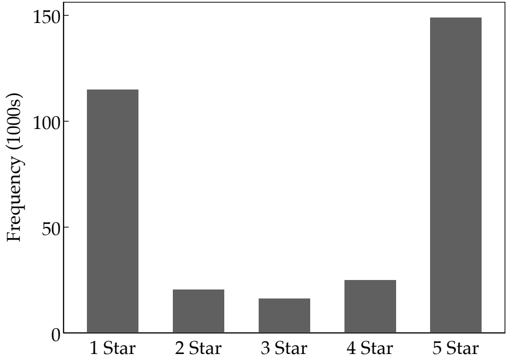
APPENDIX

Histogram of Individual Reviews



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Effects of Star Rating on Enrollment Change

	Visible Star Ratings		No Star Ratings	
	CCT Bandwidth	IK Bandwidth	CCT Bandwidth	IK Bandwidth
Estimate	0.131**	0.073**	0.030	0.031
	(0.058)	(0.034)	(0.105)	(0.061)
Robust CI	[.009 ; .278]	[.019 ; .206]	[-.228 ; .282]	[-.148 ; .24]
Bandwidth	0.13	0.39	0.13	0.30
N	916,822	2,801,989	310,307	716,328

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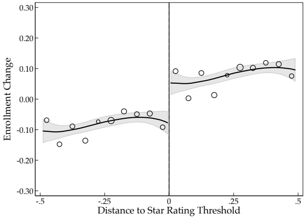
Effects of Star Rating on Enrollment Growth

	Visible Star Ratings		No Star Ratings	
	CCT Bandwidth	IK Bandwidth	CCT Bandwidth	IK Bandwidth
Estimate	0.276^{***}	0.204^{**}	0.164	0.084
	(0.100)	(0.088)	(0.233)	(0.146)
Robust CI	[.068 ; .533]	[.09 ; .48]	[-.36 ; .796]	[-.347 ; .773]
Bandwidth	0.12	0.26	0.18	0.28
N	846,362	1,995,500	420,414	688,050

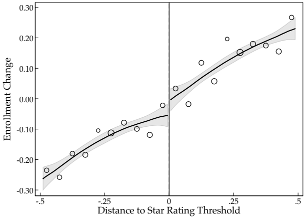
Effects of Star Rating on Changes in Enrollment: Varying the Bandwidth

	Bandwidth=0.1	Bandwidth=0.2	Bandwidth=0.3	Bandwidth=0.4	Bandwidth=0.5
Estimate	0.157**	0.110**	0.086**	0.072**	0.067**
	(0.067)	(0.045)	(0.037)	(0.034)	(0.031)
Bandwidth	0.10	0.20	0.30	0.40	0.50
N	698,624	1,431,288	2,168,005	2,877,100	3,517,643

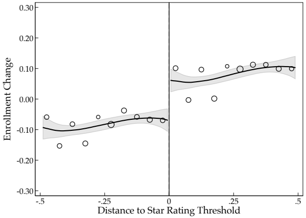
RD Effect: Additional Heterogeneity Analysis



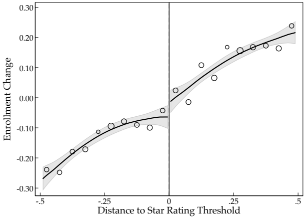
a. Low Education



b. High Education

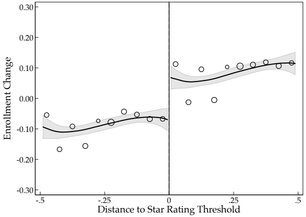


c. Low Employment

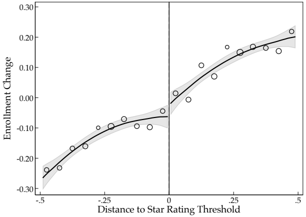


d. High Employment

RD Effect: Additional Heterogeneity Analysis



e. Low Health



f. High Health

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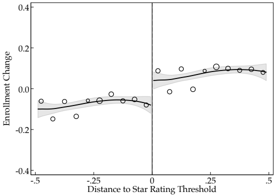
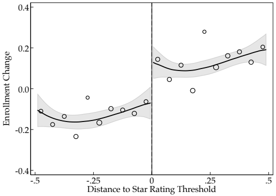
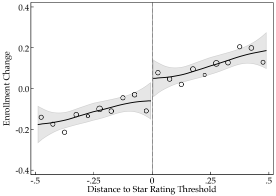
RD Effect by Income and Education



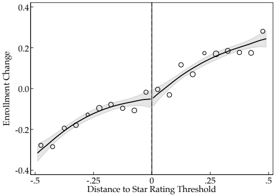
a. Low Income/Low Educ



b. Low Income/High Educ



c. High Income/Low Educ



d. High Income/High Educ

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Panel Regression Estimates

	(1)	(2)
Stars × 2	0.029∗∗∗	0.025∗∗∗
	(0.001)	(0.001)
(Stars×2) × 1(Low Income)		0.008∗∗∗
		(0.001)
GP FEs	Yes	Yes
Quarter FEs	Yes	Yes
Outcome Mean	0.17	0.17
Adjusted R2	0.011	0.011
Observations	8,475,098	8,475,098

Notes: The unit of observation is the quarterly enrollment change for an LSOA-GP. Sample is period when stars were visible. All specifications control for GP age, age squared, and number of practitioners in the GP practice. Standard errors clustered at the GP level in parentheses.

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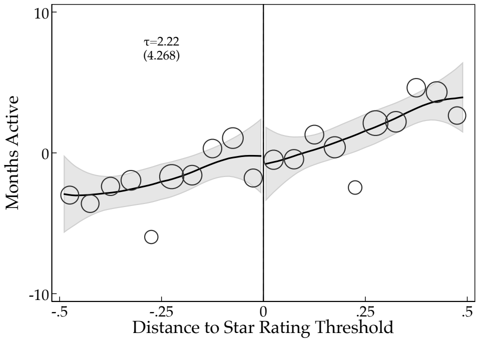
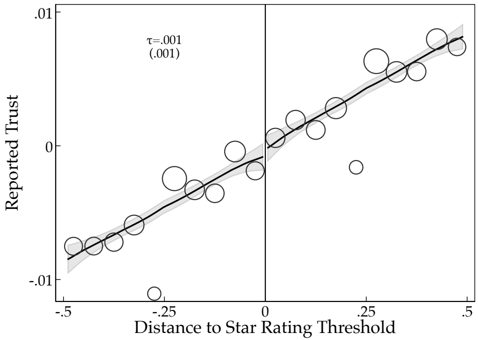
Smoothness of Covariates

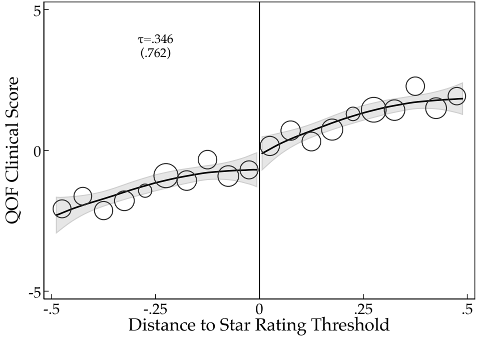


Months Active

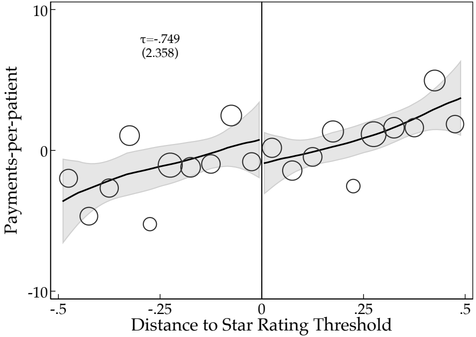


Confidence and Trust (Survey)

Smoothness of Covariates

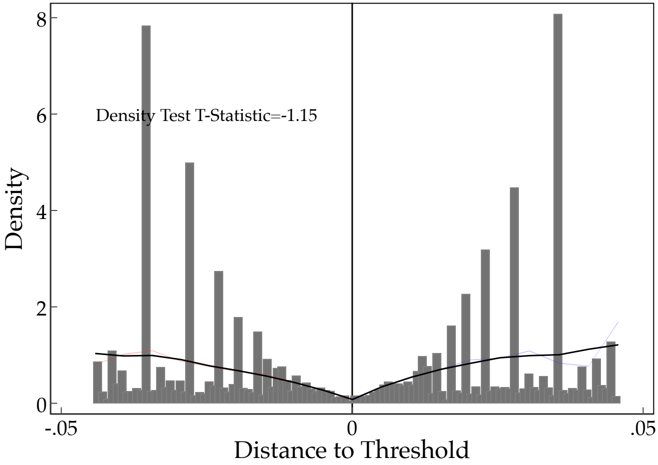


QOF Clinical Score



Payments Per-Patient

Density Tests



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