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

Zach Y. Brown<sup>1,3</sup> Christopher Hansman<sup>2</sup> Jordan Keener<sup>1</sup> Andre Veiga<sup>2</sup>

<sup>1</sup>University of Michigan

<sup>2</sup>Imperial College London

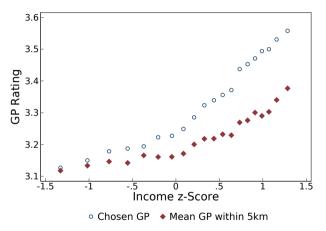
<sup>3</sup>NBER

June 2023

### 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/unobserved constraints
- Understanding 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

- 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

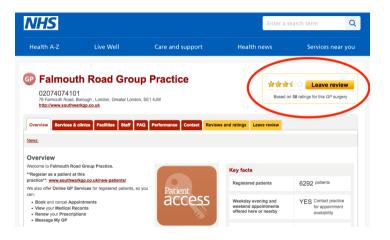
Background and Data

Regression Discontinuity Effect of Star Ratings

Empirical Model

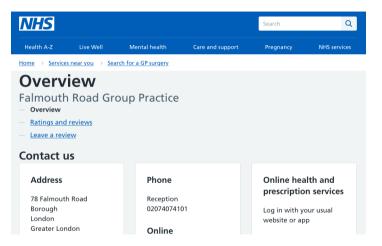
Conclusion

### 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
  - $\approx$ 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

### Regression Discontinuity Effect of Star Ratings

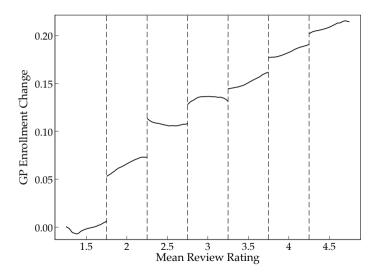
Empirical Model

Conclusion

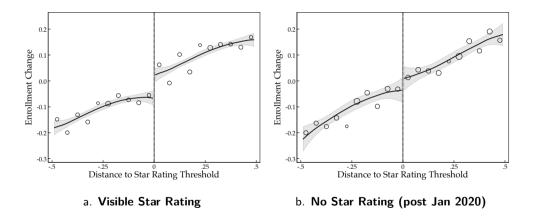
# Testing for the Impact of Star Ratings on Demand

- 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 margin helps identify 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

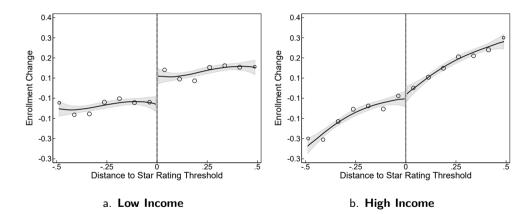


### Patients Learn from Star Ratings: Positive Effects on GP Enrollment



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

### Evidence of information gap between low and high income patients



- ullet Large jump for low-income  $\Rightarrow$  rely heavily on star ratings
- ullet Steep slope + no jump for high income  $\Rightarrow$  already informed

### Regression Discontinuity by Income

	Visible Star Ratings		No Star Ratings	
	Low Income	High Income	Low Income	High Income
Estimate	0.185*** (0.068)	0.058 (0.072)	-0.098 (0.140)	0.153 (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)

Background and Data

Regression Discontinuity Effect of Star Ratings

**Empirical Model** 

Conclusion

# 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  $s_i$  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  $\sigma_i^2$  characterizes the precision of i's information

Bayesian updating gives posterior

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

### Empirical Model

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

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

- Preference for quality,  $\beta_{1\ell}$ , is function of income
- Weight on private signal,  $\alpha_\ell$ , depends on precision  $\sigma_\ell^2$  (will be a function of income)
- $f(d_{\ell j}, X^d_{\ell t}; eta_2)$  is disutility from distance, depends on characteristics  $X^d_{\ell t}$
- $X_{jt}$  is a vector of time varying GP characteristics (GP experience, capacity)
- $\xi_j$  is a fixed effect for GP j (unobserved amenities)
- $v_{i\ell jt}$  is EV1 error capturing both error in beliefs and taste shock
- Individuals re-optimize with probability  $\theta$  (function of income/age/health), otherwise stay in their current GP

#### Indirect Inference Estimation

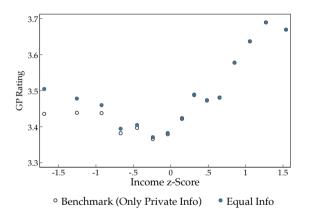
- Target four sets of moments
  - RD estimates
  - Market shares
  - Average characteristics
  - Switching rates
- For computational tractability, estimation sample is Greater London (pop 10M)

#### **Demand Estimates**

	Estimate	SE
Inertia (θ)		
Constant	-3.406	(0.002
Income	0.095	(0.002
Private Signal Precision $(\frac{1}{\sigma_r^2})$		
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 <sub>3</sub> )		
Mean physician age	0.049	(0.026
Practitioners per 1000 Patients	0.224	(0.046
Active choice fraction	0.032	

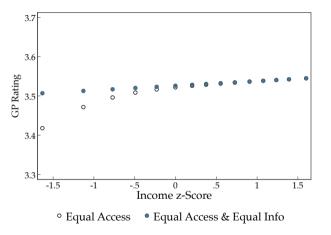
- Large degree of inertia
- High income individuals more informed
  - Precision is increasing in income
- High income less sensitive to distance
- High income slightly more sensitive to quality
- Preference for less crowded GPs

### 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

Background and Data

Regression Discontinuity Effect of Star Ratings

Empirical Model

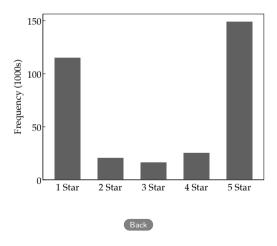
Conclusion

#### 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

#### **APPENDIX**

# Histogram of Individual Reviews



# Effects of Star Rating on Enrollment Change

	Visible Star Ratings		No Star	No Star Ratings	
	CCT	IK	CCT	IK	
	Bandwidth	Bandwidth	Bandwidth	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	



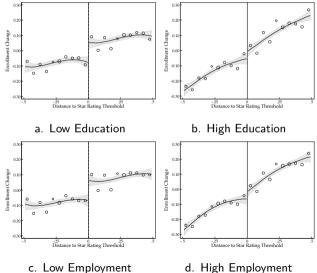
# Effects of Star Rating on Enrollment Growth

	Visible Star Ratings		No Star Ratings	
	CCT	IK	CCT	IK
	Bandwidth	Bandwidth	Bandwidth	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

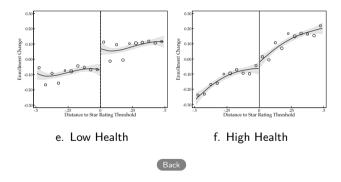
# Effects of Star Rating on Changes in Enrollment: Varying the Bandwidth

	${\sf Bandwidth}{=}0.1$	${\sf Bandwidth}{=}0.2$	${\sf Bandwidth}{=}0.3$	${\sf Bandwidth}{=}0.4$	${\sf Bandwidth}{=}0.5$
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

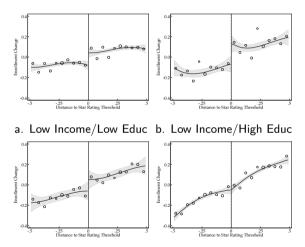
# RD Effect: Additional Heterogeneity Analysis



### RD Effect: Additional Heterogeneity Analysis



### RD Effect by Income and Education



c. High Income/Low Educ d. High Income/High Educ



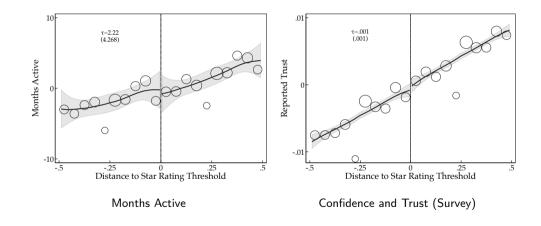
### Panel Regression Estimates

(1)	(2)
0.029 * ** (0.001)	0.025 * ** (0.001)
	0.008 * ** (0.001)
Yes	Yes
Yes	Yes
0.17	0.17
0.011	0.011
8,475,098	8,475,098
	0.029 * ** (0.001) Yes Yes 0.17 0.011

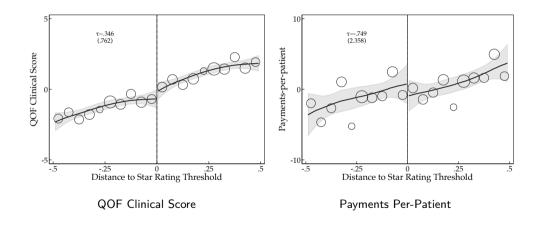
Notes: The unit of observation is the quarterly enrollment change for an LSOA-GP. Sample is period when stars were visible. All specifications control for GP age, age squared, and number of practitioners in the GP practice. Standard errors clustered at the GP level in parentheses.



#### Smoothness of Covariates



#### Smoothness of Covariates



### **Density Tests**

