# Differential Impacts of Online Ratings in the Market for Medical Services

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# Motivation: Online Reputation and Medical Services

Online ratings and reviews are an increasingly important driver of economic activity and consumer decision-making

• Top Industries: Restaurants, Hotels, Medical Services (Local consumer Review Survey 2020)

Physician services are a credence good, meaning consumers face ex-ante and ex-post uncertainty about quality

- Ex-ante uncertainty like experience goods, ratings could provide useful information
- Ex-post uncertainty unclear what information ratings include

Reputation systems could mitigate or exasperate existing disparities in the medical services industry

Studying a platform with building ratings and booking allows us to better understand important mechanisms in this market

# Introduction

#### **Research questions**

- What is the impact of ratings on demand for physician services?
- Investigate differential impact of ratings depend on other characteristics?

#### Context

• Primary Care Physicians on ZocDoc.com in 8 Metropolitan Divisions Feb 2016 - April 2017

#### Data sources

- Physician Information Profile information (PCPs) collected by scraping ZocDoc
- Patient volume Imputed from scraping physician schedules

#### Methodology

• Regression discontinuity design with multiple cumulative cutoffs (RDMCC)

Differential impact - Repeat analysis for economically interesting subgroups

- Physician Gender
- Number of Ratings (Bayesian learning)
- Hospital Affiliation (other quality signal)

# Background – Recent Literature

Impact of Ratings in Healthcare

- Patients are willing to travel further to receive care from hospitals with higher Yelp ratings (McCarthy, Sanbower, and Sánchez Aragón, 2022)
- Positive ratings increase general practitioner enrollment (Brown, Hansman, Keener, and Veiga, 2023)

Differential Impact of Ratings and Quality Signals

- Impact of ratings could be mediated by private information (Brown, et al ,2023)
- Signals of doctor quality reduce 90% of the racial gaps in willingness to pay (Chan, 2022)
- Women surgeons experience a larger drop in referrals after a patient death (Sarsons, 2017)
- Platform mechanics mediate the impact of ratings (Athey, and Kaye, in progress)

# Background on ZocDoc.com: An Online Doctor Reservation Platform

Company timeline:

- 2007: Founded
- 2015: Valued at \$1.8 billion

Revenue model charges physicians not patients

- 2015-2018: Physicians subscribe to \$300 monthly or \$3000 annual contracts
- 2018-2019: Shifted to per-booking fee

Patients can search for physicians by

• insurance, location, specialty etc. and book an appointment

Key features:

- Bundles reviews with appointments
- Verified reviews, less potential for review fraud
- Closed loop review System
- Doctors cannot screen patients

# Background on ZocDoc



# Preview of Findings

#### **Descriptive Evidence**

- Booking likelihood: More likely to be booked
- Booking speed: Booked further in advance

#### **Regression Discontinuity at 5-Stars**

- Patient volume via bookings: Approx. twice as many bookings
- Patient volume via vacancies: Approx. half as many vacancies

### **Differential Impact**

- Physician gender: Effect greatest for women physicians
- Number of ratings: Effect increases with number of ratings
- Hospital affiliation: No significant difference

#### Robustness

- Placebo tests: Effect greatest at true cutoff
- Rating manipulation: Bunching above cutoff

# Data

#### COLLECTION

#### SAMPLE RESTRICTIONS

# Data Collection

Data Collected by Crawling ZocDoc's website

Time PeriodFebruary 25, 2016 – April 17, 2017

# Profile photos processed with Microsoft Face API

#### Region – Coordinates in the following Metropolitan Divisions

Metro Division	Apts.	PCPs
Boston, MA	86,512	117
Cambridge-Newton-Framingham, MA	71,159	68
Chicago-Naperville-Arlington Heights, IL	795,000	331
Fort Lauderdale-Pompano Beach-Deerfield, FL	184,185	80
New York-Jersey City-White Plains, NY-NJ	3,629,392	1,291
San Francisco-Redwood City-South San Fr., CA	69,384	31
Silver Spring-Frederick-Rockville, MD	232,236	82
Washington-Arlington-Alexandria, DC-VA-MD	774,756	305

Appointment Sample

- Appointment type: new patient, illness, cross-listed
- Appointments on weekdays between 8am and 6pm
- At least one appointment available three weeks in advance

Physician-week sample

- "Stable" half star rating
  - 90% of observation at this rating
- Remove physicians with deleted reviews
  - More than 4 weeks with a decrease in number of reviews
- At least 8 ratings
- At least one appointment available three weeks in advance

# **Empirical Strategy**

FIRST STAGE: HALF-STAR RATINGS

DESCRIPTIVE EVIDENCE

PRIMARY SPECIFICATION

### Empirical Strategy: regression discontinuity w/ multiple cumulative cutoffs





Average Overall Rating

# Booking Likelihood by Rating



Sample: 2/24/2016-4/17/2017, primary care, min 8 ratings, with apts offered during business hours Controls: None

# Preliminary Results: Booking by Time (CDF Comparison)

- The vertical difference:
  difference in percent of
  appointments booked at a
  given number of days in
  advice.
- The horizontal differences: The difference in how many days in advanced the same percent of appointments were booked.



# Empirical Strategy: Primary Specification

#### **Observation level:** Physician-week

Dependent variable: Weekly patient volume based

- Inverse Hyperbolic Sign (IHS) of bookings
- IHS vacant appointments (alternative)

#### Running variable: Average overall rating

**Covariates:** Market-week, IHS(offered appointments), number of location, appt length and type no. reviews, hospital affiliation

#### Methods:

- Asymmetric data-driven MSE-optimal bandwidth selectors
- Triangular kernel
- Mass point adjustments
- Bias-corrected RD estimates with robust variance estimator
- Cluster-robust nearest neighbor variance estimation clustered on physician (panel data)

# Results

PRIMARY SPECIFICATION

ALTERNATIVE SPECIFICATIONS

DIFFERENTIAL IMPACTS

ROBUSTNESS CHECKS

# Impact of Ratings on Patient Volume: Approx. Doubling of Bookings

![](_page_17_Figure_1.jpeg)

Sample average within bin — Polynomial fit of order 1

Details

# Impact of Ratings on Patient Volume: Approx. Doubling of Bookings

![](_page_18_Figure_1.jpeg)

Specification: data-driven asymetric bandwidth, triangular kernal, NNcluster on physician

Vacancy Results

#### RD Plot by Physician Gender: Women Have More Bookings at 4.5 and 5 Stars

![](_page_19_Figure_1.jpeg)

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# Differential Impact of by Gender: Effect Greatest for Women

![](_page_20_Figure_1.jpeg)

Details

# Differential Impact of by Ratings: Effect Increases with No. Ratings

![](_page_21_Figure_1.jpeg)

Specification: data-driven asymetric bandwidth, triangular kernal, NNcluster on physician

# Differential Impact of by Hospital Affiliation: Similar Effects

![](_page_22_Figure_1.jpeg)

Specification: data-driven asymetric bandwidth, triangular kernal, NNcluster on physician

### Robustness: Placebo Test of Main Result

![](_page_23_Figure_1.jpeg)

Controls: market-week, no. locations, appt length, appt type, no. reviews, hospital affiliation Sample: 2/24/2016-4/17/2017, primary care, min 8 ratings, with apts offered during business hours 21 days in advance, stable ratings, excludes profiles with >4 rating removals Specification: data-driven asymetric bandwidth, triangular kernal, NNcluster on physician

# Robustness: Visible Bunching Above Cutoff

![](_page_24_Figure_1.jpeg)

Sample: 2/24/2016-4/17/2017, primary care, min 8 ratings, with apts offered during business hours 21 days in advance,

# Conclusion

#### SUMMARY OF RESULTS

DISCUSSION & MECHANISMS

# Summary of Findings

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# Discussion: Potential Mechanisms

Gender: Effect greatest for women physicians

- But not closing a gender gap
- Correlated preferences
  - Ex: Gender, rating, and wait time
- Platform recommendation system

Ratings: Effect increases with number of ratings • Consistent with Bayesian learning

Hospital Affiliation: Similar Effects

Extend to analysis to other cutoffs

Differential impact by apparent race and age

Robustness

- Mass at cutoff
  - "Donut" regression discontinuity
- Covariate balance

# Appendix

# Booking by Time (CDF Comparison)

Use a pilot bandwidth of .1 to compare these cdfs of physicians just above and just below the 4.75 threshold to have five stars.

![](_page_30_Figure_2.jpeg)

# Patient Volume by Star Rating: 4, 4.5, and 5-Stars

![](_page_31_Figure_1.jpeg)

stable ratings, excludes profiles with >4 rating removals

### Impact of Ratings on Patient Volume: Fewer Vacancies

![](_page_32_Figure_1.jpeg)

Specification: data-driven asymetric bandwidth, triangular kernal, NNcluster on physician

**Booking Results** 

# Booked Appointments by Page Rank Proxy

We are also interested in platform mechanics. Here, we take advantage of the fact that page rank is a function of availability.

**Observation Level:** Physician-day

Dependent Variable: Count of appointments booked that day

**Variables of Interest:** Proxy for page rank with the number of same day appointments available, and the lag of same day appointments available.

**Intuition:** If page rank has no effect, we might expect these coefficients to be negative. A positive coefficient suggest page rank is indeed important.

**Controls:** Number of available appointments, physician FE, and time FE.

## Booked Appointments by Page Rank Proxy

![](_page_34_Figure_1.jpeg)