// NO.21-075 | 10/2021

DISCUSSION PAPER

// MICHAEL KUMMER, ULRICH LAITENBERGER,
CYRUS E. RICH, DANNY R. HUGHES, AND TURGAY AYER

Healthy Reviews! Online Physician Ratings Reduce Healthcare Interruptions

Healthy reviews! Online physician ratings reduce healthcare interruptions[*]

Michael E. Kummer[†] Ulrich Laitenberger[‡] Cyrus E. Rich[§]
Danny R. Hughes [¶] Turgay Ayer[‖]

August 26, 2021

Abstract

We show that review platforms reduce healthcare interruptions for patients looking for a new physician. We employ a difference-in-differences strategy using physician retirements as a "disruptive shock" that forces patients to find a new physician. We combine insurance claims data with web-scraped physician reviews and highlight a substantial care-gap resulting from a physician's retirement. We then show that online physician reviews reduce this gap and help patients find a new physician faster. Our results are robust to including a variety of controls and various instruments for the availability of physician reviews, but are not found for patients of nonretiring physicians. By reducing interruptions in care, reviews can improve clinical outcomes and lower costs.

JEL Classification: I1, I11, I12, O33

Keywords: Healthcare, Online physician ratings, Online physician reviews, Care-gap.

---

[*]This work was supported by the grant "Review Platforms & Improved Health Care" (ICOL - 512660E) by the American College of Radiology, Reston VA. We thank participants of the seminar of the CBESS group and in particular Chris Forman and Michelangelo Rossi for helpful comments. The authors alone are responsible for the content.

[†]University of East Anglia, Georgia Institute of Technology and ZEW Mannheim; e-mail: michael.kummer@econ.gatech.edu.

[‡]i3, Telecom Paris, Institut Polytechnique de Paris, 91120 Palaiseau, France and ZEW Mannheim; e-mail: ulrich.laitenberger@telecom-paris.fr

[§]H. Milton Stewart School of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, USA. e-mail: crich@gatech.edu

[¶]Georgia Institute of Technology; e-mail: danny.hughes@econ.gatech.edu

[‖]Scheller College of Business, Georgia Institute of Technology, Atlanta, Georgia 30308, USA; e-mail: ayer@isye.gatech.edu

1 Introduction

Finding good health-care providers is not easy, because health-care services are credence goods (Darby and Karni, 1973). Patients traditionally lack objective information about the quality of physicians. Many patients rely therefore on word-of-mouth recommendations from friends and relatives (Tu and Lauer, 2008) when selecting new primary care physicians, and even physicians rely on their inside information for referrals (Hackl et al., 2015). The lack of information is especially problematic for patients who need to choose a new provider because they changed insurance plans, their residence, or experience other life changes. Such patients might delay a visit to seek care and treatment, which can result in suboptimal health outcomes (Barach et al., 2020). The retirement of a primary care physician decreases their patients' future primary care utilization, and increases specialty care, emergent care, and charges (Sabety et al., 2021).

In this paper, we show that health-related online reviews help patients to overcome the friction associated with choosing a new physician. We analyze patient behavior and document a substantial care-gap - a delay in finding care - before patients visit a new physician. We further show that online physician reviews shorten this care-gap and help patients to find new physicians faster. We leverage the retirement of physicians as a "disruptive shock" that induces a patient to search for a new physician. We analyze the time lapse until patients visit a new physician after their physician has retired. We identify the effect of reviews using a difference-in-differences (DiD) strategy. In this strategy, we compare cities with a large accumulation of online reviews to cities with very few online reviews.

We conduct our analysis by augmenting a unique data set on individual-level patient claims with information from a major review platform for physicians (yelp.com). The combined database is ideally suited for studying our key research question. The medical claims data covers the entire population of patients associated with the included insurance carriers (over 55 million unique individuals). Through the pattern of insurance claims we can track whether patients experience an interruption to their care after their physician's retirement. The data about online reviews indicates the availability of information about physicians in a patient's city, and how that availability changes over time.

The empirical challenge when measuring the effect of reviews on patient behavior is that it is difficult for a researcher to observe *when* patients want to find a new physician. Most patients typically have stable relationships with their physicians, making a patient searching for a new physician a low-frequency event. Focusing on patients of retiring physicians allows overcoming this challenge: First, the retirement of a physician requires patients to search for a new physician. Second, researchers can observe retirements. Our strategy focuses on a specific type of interruption, but we expect other major life changes of patients to induce similar interruptions.

We document two main findings. First, physician retirements cause disruptions in care. Specifically, physician retirements increase the gap between two visits by more than 140 days on average. Second, this gap is shorter when online reviews are available. In particular, the gap in time between two visits is 30.7 days shorter on average in the presence of online reviews, and patients are 7 percentage points more likely to visit a new physician within 15 months of their current physician retiring.

We demonstrate the robustness of our findings by showing that the effect becomes insignificant for patients of nonretiring physicians, highlighting that no shifts in underlying trends occurred in the pretrend analysis and by controlling for various alternative and potentially omitted variables (including income, education, broadband availability, and the number of physicians in the county). Moreover, we apply an instrumental variable (IV) strategy that exploits reviews in the same city for other professions to rule out the possibility that the effect is driven by physician-specific technology adoption.

Our results have several implications for research and policy. Review platforms appear to have a decisive impact on patients' health-related decision making when patients lose their physician. Our results suggest that insurers and public health organizations can motivate patients to receive more continuous care when their relationships get disrupted. Scaling online review platforms could be a way to reduce disruptions in care, which can have severe negative effects on a variety of clinical outcomes (Barach et al., 2020). Moreover, high quality online reviews promise to be a cost-effective measure to improve access to care since review content is user generated and can be made widely available at low cost. Lastly, we demonstrate that it is feasible to identify a precise mechanism through which online reviews affect patient outcomes, and future research can build on this step to quantify the link between online reviews and clinical outcomes.

1.1 Literature review and study contributions

By highlighting the care-gap after physician retirements and showing that reviews *quicken* the process in which patients choose a new physician we make several contributions.

Online and medical reviews. We contribute to the literature that has shown how online reviews affect the behavior of individuals and firms (Chevalier and Mayzlin, 2006; Duan et al., 2008; Forman et al., 2008; Cabral and Hortacsu, 2010; Luca, 2011; Helmers et al., 2019; Reimers and Waldfogel, forthcoming). They achieve this effect by conveying accurate information on the quality of goods or services and informing consumer choices (Hu et al., 2006; Lu and Rui, 2018; Yin et al., 2016; Howard et al., 2017; Sahoo et al., 2018; Choi et al., 2019). Our paper contributes by highlighting the ability of online reviews to increase overall economic efficiency in health care.

We also contribute to the literature on how online health-related information can affect patient choices and health outcomes (Billari et al., 2019; Amaral-Garcia et al., forthcoming). A series of papers have highlighted the correlation between physician reviews and physician quality, and shown that physician demand is affected by online reviews (Greaves et al., 2012; Gao et al., 2012; Emmert and Meier, 2013; Lu and Rui, 2018; Saifee et al., 2020; Chen and Lee, 2021; Luca and Vats, 2014; Lu and Wu, 2019; Kaye, 2020; Bensnes and Huitfeldt, 2021; Chen and Lee, 2021; Xu et al., 2021). Our findings expand beyond prior knowledge, because we highlight that reviews do not only influence which physicians are chosen, but they also help patients to choose *any* physician and to make their choice faster.

2 Background: physician reviews in the US

Physician review sites. Patients increasingly rely on physician review websites to find new health-care practitioners. Customer surveys suggest that about 72% of consumers use physician rating sites as the first step in finding a new physician,[1] 80% trusted online reviews as much as personal recommendations from acquaintances, and 47% preferred out-of-network physicians with better reviews over in-network physicians with comparable qualifications but poorer reviews. Holliday et al. (2017) find that 53% of physicians have visited a physician review website, potentially in an effort to improve patient satisfaction.

Accordingly, over 70 different websites host reviews of physicians in the US.[2] This increased availability of reviews is driven by both new dedicated sites (e.g. Healthgrades.com, RateMDs.com, and ZocDoc.com), and established platforms that added a platform for physician reviews (e.g. Google, Facebook, and Yelp). In 2010 the Centers for Medicare & Medicaid Services launched "Physician Compare," which saw lower usage than expected.[3]

Crowd-based ratings on Yelp. Yelp is a website where consumers can leave reviews for a variety of businesses. It is widely available across the US and has high coverage of physicians. On Yelp, users can freely read and write reviews of physicians. Users can give ratings from 1 to 5 stars and add a narrative review. By mid 2020, Yelp users have contributed over 21 million health-related reviews.

3 Empirical strategy

Hypothesis development: Our main hypothesis is that online reviews affect patient choices by facilitating the search for a new physician. We expect that online reviews decrease search cost and reduce patients' uncertainty about the quality of physicians.

[1] 70% strongly prefer physicians with positive reviews, and 61% avoid physicians with negative reviews; See Reviewtrackers and NRCHealth.com

[2] See ReviewConcierge, archived under Web Archive.

[3] See "Physician Compare (Updated), " Health Affairs Health Policy Brief, Dec, 2015, available here.

To formalize this idea, consider time-constrained patients forced to find a new physician. Denote the net benefit of searching for and contacting a physician as v_p. The net benefit v_p depends negatively on the patient's search cost c_s and positively on the new patient's expected match value $E(q)$ with the physician.

Assume (without loss of generality) that patients do one task per day and have an alternative action of value v, which is randomly drawn from a continuous distribution. Each day, patients choose the task with the highest net value out of v, v_p. The probability of a patient doing something other than finding a physician is given by $P(v_p \leq v)$. The expected number of days until a patient searches for a physician can be calculated as a probability-weighted average of the different infinite possible outcomes:

$$E(DAYS) = (1 - P(v_p \leq v)) \cdot 1 + P(v_p \leq v) \cdot (E(DAYS) + 1) \tag{1}$$

The expected number of days is given by $E(DAYS) = 1/(1 - P(v_p \leq v)$. The probability that the physician search is less attractive than the alternative action enters negatively in the denominator, such that a higher net-value of finding a physician v_p implies a lower expected number of days until the patient engages in search and, consequently, a shorter inter-visit duration. Reviews increase v_p by reducing the search cost (c_s), and by raising patients' expected match value $E(q)$.[4] This mechanism leads to fewer days until the next visit. We derive two hypotheses from this mechanism:

H1: If online reviews are available, then patients who need to find a new physician are more likely to do so in any given time window.

H2: If online reviews are available, then patients who need to find a new physician will find their physician faster, conditional on searching.

Estimation approach: Our identification strategy relies on physician retirements as a disruptive shock that forces patients to search a new physician. We use this approach, because patients will generally stick to their existing relationships.[5] Physician retirements have been shown to a negative effect on patients (Lam et al., 2020), and we will document that physician retirements induce a gap in treatment. While a physician's retirement is a specific shock, similar disruptive events can be observed when patients move to a new location, change their insurance plan, or develop a new condition.

To analyze whether online reviews *shorten* the care-gap, we use a DiD approach that quantifies the effect of having a high number of online reviews for physicians in a given city. We estimate linear models with observations at the level of patient p in period t of

[4] Reviews improve the expected match value, because they allow patients to sample their physician from a pre-selected set of physicians with satisfactory reviews, rather than sampling randomly.

[5] Patient inertia for insurance plans (Samuelson and Zeckhauser, 1988) arguably extends to physicians.

the form

$$y_{p,t} = \alpha' post_t + \beta' did_{p,t} + \gamma' X_{p,t} + \xi_c + \varepsilon_{p,t}. \quad (2)$$

We estimate this model for two dependent variables $y_{p,t}$: first, a binary variable that takes a value of 1 if a patient saw a new physician within 15 months ($fup15$), and, second, the time until the next physician visit measured in days ($DAYS$). Although $fup15$ is a binary variable, we use a linear probability model (LPM) because this allows us to obtain consistent estimates while including a large number of fixed effects and interaction terms.

The term $post_t$ is an indicator variable that takes a value of 1 if the retirement is in the treatment period.[6] The DiD-term $did_{p,t}$ takes a value of 1 if an observation was made in a city with reviews and in the period after treatment (post period). This indicator is built using only reviews before the patients choice to avoid reverse causality. The control variables $X_{p,t}$ capture patient (age, gender) and physician (specialty) characteristics.

Note that we cannot match reviews to physicians to preserve anonymity, but we observe the presence of reviews at the city level. Nevertheless, even our city-level measure of reviews can capture various channels of the usefulness of reviews in reducing the care gap after a physician retires. We discuss measurement concerns in Appendix C.

Greater availability of Yelp reviews could be associated with a higher degree of education or engagement of citizens in managing their health care. These factors are likely to be relatively constant over time. To account for unobserved time-constant heterogeneity among cities, we include fixed effects for the city where the patient lives ξ_c. We discuss potential unobserved heterogeneity in cities over time in the following subsection.

Identification The key challenge in our analysis is identifying whether a causal link exists between the presence of online physician reviews and the time it takes for patients to select their new physicians. The main hindrance to identification is endogeneity caused by i) omitting important explanatory variables and ii) selection into treatment, which we discuss below. In Appendix C we discuss these and other concerns in greater detail.

Omitted variable bias. We use four strategies to address a potential OVB: (1) city-fixed effects in the DiD regression control for any time-invariant factors (geography, city layout, or physical infrastructure,...). (2) we need to control for time-varying factors that may affect the time it takes patients to find a new physician after a retirement. Such factors could be changes in the composition of the population (e.g., age, education, income), technological progress (e.g., improved infrastructure, broadband adoption, adoption of ICT), asymmetric government or insurance policies to shorten the care gap (e.g. reduced entry barriers for physicians), and changes in health-related attitudes. We therefore add control variables for broadband availability, income, education, and the number of physi-

[6] In Appendix B.2. We include time fixed effects to assess whether annual periodicity or a trend over time can explain the observed effect and show that the conclusions remain largely unchanged.

cians. (3) we run a placebo test on patients of *nonretiring* physicians. This placebo analysis documents that the time between visits has not generally decreased in treated cities. The control variable analysis and the placebo analysis are further supported by our pre-trend analysis (Figure 2), which highlights no shifts in the underlying trends until 2012. (4) we take additional precaution and run an IV two-stage least squares (2SLS) estimation based on the presence of reviews in other Yelp categories. This IV addresses any omitted variable bias or reverse causation due to physician-driven factors, that might have begun after 2012 and changed more quickly in treated cities than untreated cities.

Because of these four measures, any remaining omitted variable bias would have to be due to a variable that (1) is time-varying, (2) is correlated with online reviews and the time between visits, (3) is not driven by physicians directly, (4) would not be seen in the pre-trends until 2012 and, (5) influences the time between visits for patients of retiring physicians, but not for patients of nonretiring physicians.

Selection into treatment. Two more concerns arise because treatment was not randomly assigned. First, unobserved factors might partially govern which cities received treatment (e.g. physicians' technology adoption such as appointment booking systems). This concern is akin to OVB, just with a focus on drivers of review provision. It is addressed by our robustness checks in Table 3. Second, treatment could be more effective in treated places. and less effective in untreated places - even if they were created exogenously. Hence, we interpret our results as Average Treatment Effect on the Treated (ATT), but argue that this issue will disappear as adoption progresses.

In an Online Appendix (C) we discuss our identification strategy in greater detail.

4 Data

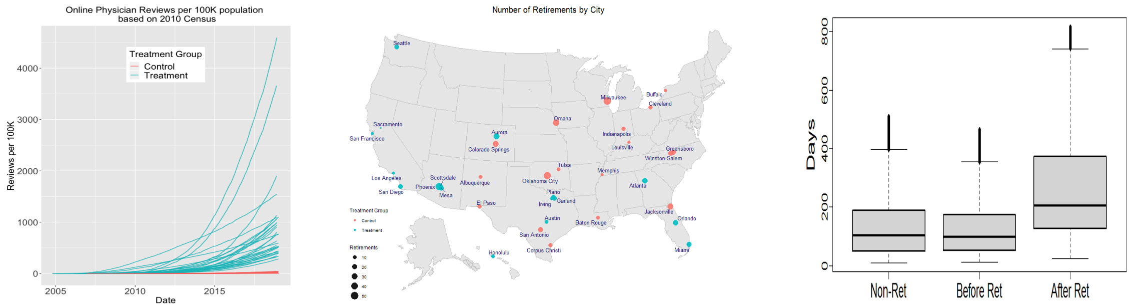
4.1 Sources and preparation

Our analysis combines patient-physician-level data with city-level data on online reviews.

Physician review data and the definition of the control and treatment group. We use data from the website Yelp.com to measure the availability of physician reviews across the United States. Starting from the top 100 US cities by population, we selected the 30 cities with the lowest and highest review accumulation per capita. The full list of cities can be found in Tables A2 and A3 in Appendix A.2, where we describe the details of our procedure. Until the late 2000s - our pre-treatment period - the number of reviews per capita was nearly 0 for all cities.

The left panel of Figure 1 shows that our procedure was effective, as reviews indeed became widely available in the treated cities but not in the cities in our control group. The central panel of Figure 1 shows the cities in which we identified physician retirements, and the boxplot on the right highlights the care-gap that results from a physician's retirement. The average number of days until the next visit after a retirement exceeds 275 days, whereas the average time between visits without a physician retirement is 137.75 days. Similarly, the average time between visits *before* a retirement is 125.02 (see Figure 1).

Figure 1: Cities in the sample, review growth, and care-gap.



NOTES: The left-hand figure compares the growth in the number of reviews per 100,000 inhabitants in treated and untreated (control) cities. The central figure shows the location of the treated and untreated cities in our sample; the circle's size reflects the number of retirements detected. The boxplot on the right compares the distribution of the time between patient visits for nonretiring physicians (left) to retiring physicians before (middle) and after retirement (right).

Patient data. To observe patients' physician choices and the time until the next visit, we use Optum's de-identified Clinformatics® Data Mart Database (CDM), which is a commercial and Medicare Advantage claims database with beneficiaries in all 50 US states from 2007 to 2018. Claims are created whenever patients visit their physician and the physician charges the patients' health insurance for the payment (in full or in part). The database includes over 55 million unique patients over the 10+ years captured, and roughly 15-18 million patients in a given year.

We aggregate patient claims to daily visits, using data from October 2007 to March 2010, and from October 2015 until March 2018[7] We focus our analysis to specialties that are considered to benefit from regular visits and preventative care: cardiology, dermatology, infectious disease, gastroenterology, and psychiatry. We also use the claims data to infer when a physician retires, and identify retirements that occur in the twelve central months of both data windows (2008Q2 to 2009Q1 vs. 2016Q2 to 2017Q1).[8]

We retain only cities with observations before and after treatment, which leaves us with 16 treated and 18 untreated cities. The location of the cities in this data set can be seen on the right-hand side of Figure 1, where blue bullets indicate cities in the treated group, red bullets indicate cities in the control group. The size of the bullet indicates the number of physician retirements we observe in each city.

[7] In Appendix B.1, we report the results for alternative pre-treatment periods.

[8] The procedure is based on identifying abrupt changes from activity to inactivity over a longer period. We describe the details in appendix section A.1.

4.2 Descriptive statistics

The unit of observation in our main dataset is a patient of a retiring physician, either at the time of the first visit to a new physician, or the end of our observation period. Table 1 shows the main variables in our study. Panel A gives information about the size of our treatment group and sample period. About 44% of the patients that are affected by a retirement are observed in 2014-2017, which we define as our treatment period (*post*), and 45% of the patients in our sample live in the cities in the treatment group (*treat*). Our data cover more patients from untreated cities than treated cities, and 15% of patients are in the *treat* group in the *post* period (DiD).

Table 1: Descriptive statistics.

	Mean	Min.	Max.
Panel A: Treatment definition			
post	0.44	0	1
treat	0.45	0	1
DiD	0.15	0	1
Panel B: Patient, city and physician characteristics			
Female	0.55	0	1
Age (years)	64.7	0	89
Age below 20 years (*age_u20*)	0.03	0	1
Age 20 to 39 years (*age_2039*)	0.09	0	1
Age 40 to 49 years (*age_4049*)	0.07	0	1
Age 50 to 64 years (*age_5064*)	0.17	0	1
Age 65 to 74 years (*age_6574*)	0.27	0	1
Age 75+ years (*age_75*)	0.37	0	1
Cardiology (*card*)	0.53	0	1
Dermatology (*derm*)	0.29	0	1
Infectious Diseases & Gastroenterology (*infc_gast*)	0.15	0	1
Psychiatry (*psych*)	0.03	0	1
Panel C: Main outcome variables			
Follow-up visit in 15 month (*fupm15*)	0.398	0	1
Time between visits (*days*)	275.32	3	1,401

NOTES: The table shows the summary statistics of the main estimation sample used in Table B6. The number of observations is 27,113.

Patient characteristics. In our data, 55% of the patients are female, and patients are on average 65 years old when their physician retires. Only 36% of the patients in our data are under 65, 27% are between 65 and 75, and 37% are 75 and over. Patients between 20 and 49 are the reference category in our regression analysis. Consistent with the age structure, most visits concern cardiology (53%) and dermatology (29%). The remaining visits concern infectious diseases and gastroenterology (15%) and psychiatry (3%).

Time between visits and "care-gap" after retirements. Our main outcome variable is the time that elapses between two visits. Only 40% of patients in our data visit a new physician within 15 months of their last visit to a retiring physician.[9] We observe a large care-gap after a physician retires.

The average number of days until the next visit after a retirement exceeds 275 days, whereas the average time between visits without a physician retirement is 137.75 days. Similarly, the average time between visits *before* a retirement is 125.02 days (see also Figure 1 and Table A5 in Appendix A.4).[10]

The impact of reviews: descriptive evidence. In Table 2, we compare the relative frequency of a follow-up visit and the days between visits for patients in the four treatment groups (pre- vs. post and treatment vs. control group). Although follow-up visits within 15 months seem to be less likely over time, the time between visits increases in the control group but decreases in the treatment group. Figure A1 in the Appendix shows the distribution of the time between visits for each group of patients, confirming that the mass of long time between visits decreases.

Table 2: Relative frequency of follow-up visit and time between visits.

	All	Control		Treatment	
		Pre	Post	Pre	Post
Follow-up visit (15m)	0.398	0.445	0.435	0.353	0.336
Intervisit time (days)	275.32	271.71	282.18	274.18	268.48

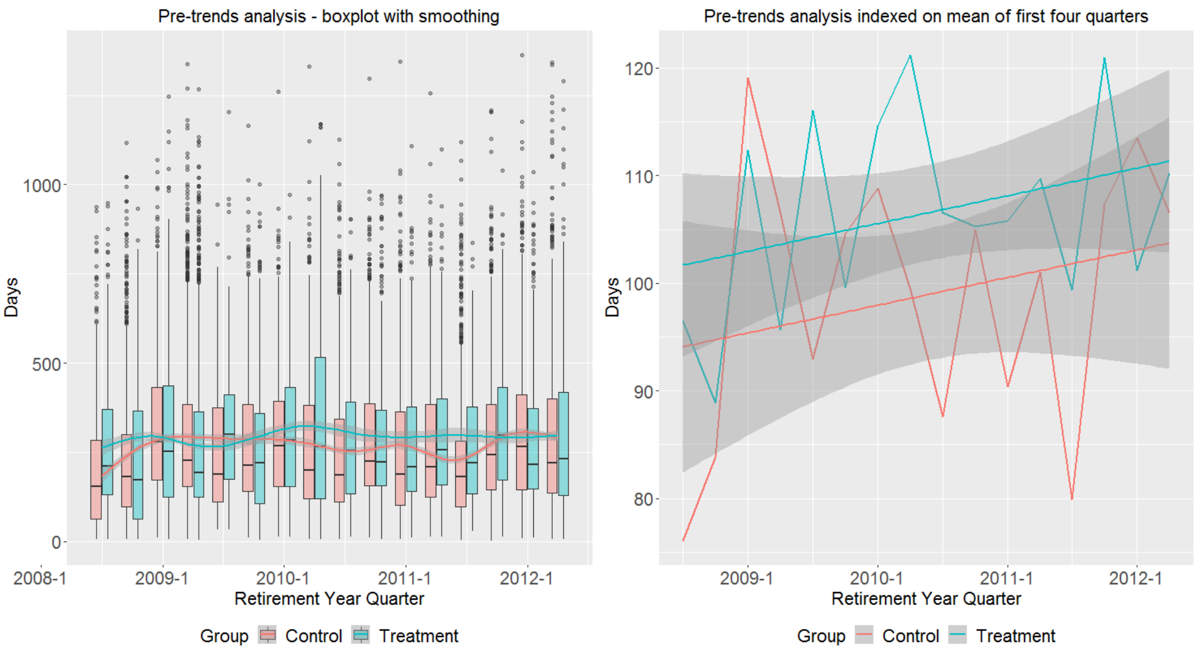
NOTES: The table shows the mean frequency of a follow-up visit within 15 months as well as the mean time between visits in days for both treatment groups in each period.

Analysis of the pre-treatment trends. Our DiD estimation requires verification of the parallel trends assumption. The left side of Figure 2 compares the quarterly averages of the time between visits after a retirement in treated and untreated cities. We provide this comparison for the year used in our pre-treatment period (2008Q2 to 2009Q1) and the subsequent three years. The right panel applies linear smoothing and shows confidence intervals. The average time between visits is slightly longer in treated cities, and grows slightly *faster* in cities that receive treatment by reviews, but the difference is small and insignificant. The visual impression is confirmed by a regression that analyzes interactions of the treatment dummy with a time trend or retirement quarters (shown in Appendix Table A6). There is no statistically significant difference in the development of the number of days between visits over time.

9 In Appendix B.3 we show that our findings are robust for alternative time cutoffs (3 to 12 months).

10 For nonretiring physicians, we randomly fixed a placebo retirement date and computed the mean time between visits before and after the placebo retirement. For retiring physicians, we do the same before retirement, and measure the time until the next visit (to a new physician) after retirement.

Figure 2: Pre-treatment Trends.



NOTES: In this figure we analyze whether a patient's time between visits after their physician retires evolves similarly over time for patients in cities with and without reviews. The left figure shows quarterly box plots of the distribution of these patients' time between visits by treatment and control groups. The right figure shows the linear trend of the average time between visits per patient, indexed by the average time between visits during the first four quarters (our pre-period).

5 Results

5.1 Effect of reviews on physician visits

In columns 1-2 of Table 3, we document our main regression result: Online reviews reduce the care gap that patients experience after their physician retires. We document this for two outcome variables: the probability of a follow-up visit within 15 months (col. 1) and the number of days until the next visit (conditional on observing a visit; col. 2). All specifications include specialty and city fixed effects, and control for a patient's age and gender.[11] Before turning to our main finding, we note that patients in the post-period are less likely to pursue continuous care within 15 months and they have their follow-up visits later across all specifications.

When reviews are available, patients in cities in our treatment group are on average 7 percentage points (p.p.) more likely to have a follow-up visit in the next 15 months (Col. 1) Column 2 of Table 3 summarizes the analysis of our second main outcome variable: days between visits.[12] The result is consistent with the findings in column 1. The main effect in column 2 shows that the time between visits decreases by 30.7 days with reviews.

We provide complementary analyses and robustness checks in Appendix B. Our results

[11] These coefficients are shown in Appendix Table B6.
[12] The unit of observation in these regressions is a patient who saw a new physician within 15 months.

Table 3: Effect of reviews on follow-up visit (LPM) and time between visits.

	Base model		*OVB Controls*		*IV (plumber rev.)*		*Placebo*	
	Follow-up	DAYS	Follow-up	DAYS	Follow-up	DAYS	Follow-up	DAYS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DiD	0.070^{***}	-30.685^{***}	0.047^{**}	-28.656^{**}	0.116^{***}	-55.459^{***}	-0.008^{**}	-3.574
	(0.014)	(9.131)	(0.019)	(13.063)	(0.020)	(12.685)	(0.004)	(2.244)
post	-0.057^{***}	24.943^{***}	-0.056^{**}	32.816^{**}	-0.060^{***}	25.739^{***}	0.029^{***}	2.722^{*}
	(0.009)	(5.376)	(0.023)	(16.376)	(0.010)	(5.844)	(0.003)	(1.637)
Education (%)			0.001	2.081				
			(0.002)	(1.492)				
Income p.c.			-2.285^{**}	817.864				
			(1.039)	(864.906)				
Poverty (%)			-0.011^{***}	6.411^{***}				
			(0.003)	(2.280)				
# Physicians			0.00001^{*}	-0.003				
			(0.00000)	(0.002)				
Broadband (%)			0.040	-22.086				
			(0.062)	(48.084)				
Ref. Category	20-49	20-49	20-49	20-49	20-49	20-49	20-49	20-49
Dem. Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,113	13,007	23,038	10,719	27,113	13,007	288,436	160,935
IV 1st Stage					*(OLS coefficients)*			
#Plumber Revs.					0.051^{***}	0.059^{***}		
					(0.0002)	(0.0004)		
marg. adj. R^2					0.155	0.164		

NOTES: In this table, we analyze the effect of reviews on a patient's likelihood to follow up with a new physician (odd columns) and the number of days until this follow-up visit occurs (even columns) after their old physician retires. Columns 1 and 2 show the baseline result (reference category: patients age 20-49 years). In columns 3-4 we include controls that could be omitted confounding factors. Columns 5-6 show an instrumental variable regression using a city's number of online reviews for plumbers as the IV. Columns 7-8 show the results of a placebo test for patients of nonretiring physicians. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01.

remain consistent if we (1) vary the pre-treatment time-window (Section B.1), (2) use different time fixed effects (Section B.2), or (3) use shorter cutoffs for the follow-up regression (Section B.3). We also analyze how the effects vary by age (Section B.4), specialty (Sections B.4 and B.5) and by population growth (Section B.6). The effect is driven by cities with faster population growth, and by visits concerning cardiology and gastroenterology. Moreover, the effects are strongest for young patients (20-49) and for very old patients (75+) who might receive help from younger friends and relatives.

5.2 Identification and robustness checks

Our main argument highlights that reviews are particularly useful when existing physician-patient relationships are disrupted. In the subsequent sections, we examine the possibility that our results are driven by factors that are correlated with the presence of reviews and also affect the time between visits.

First, to mitigate the concern that our results are due to the potential selection into treatment, we report instrumental variable estimations based on (1) Yelp reviews for other professions and (2) the share of young physicians in a city. Second, to rule out the possibility that our results are driven by an omitted variable, we (1) add further control variables and show that the results do not qualitatively change, and (2) conduct a placebo test in which we estimate the main regressions for patients of *nonretiring* physicians. This test allows us to rule out any other omitted factors that generally decrease the time between visits in a location, regardless of retirements.

5.2.1 Instrumental variable specification

Reviews for physicians could emerge due to unobserved technology adoption by physicians that coincides with improved follow-up rates and shorter intervals between visits. We address this concern using reviews that are not health related as an instrument. Reviews in other categories are not driven by health-specific developments but are predictive of reviews for physicians. We collected the number of Yelp reviews for plumbers and hairdressers at the city level. Appendix Tables D7 and D8 show that reviews for plumbers and hairdressers are highly predictive of reviews for physicians.[13] The exclusion restriction is easily defended, because reviews for plumbers plausibly do not affect the time between physician visits directly.

Columns 5 and 6 in Table 3 report the results when instrumenting the availability of physician reviews with the number of plumber reviews in the same city. Our main results are confirmed: reviews have a strong positive effect on the probability of follow-up, and shorten the time between visits. The respective coefficients are larger in magnitude than with ordinary least squares (OLS). With reviews, the follow-up probability increases by 11.6 p.p., and the time between visits reduces by roughly 55 days.

In Appendix D, we document descriptive statistics for the instruments in Table D1, and compare the first- and second-stage results when reviews for hairdressers, rather than plumbers, are used as instruments (Table D3). We also use reviews per capita, instead of the absolute number (Table D4). The results consistently point to a higher likelihood of a follow-up visit and a shorter time between visits. In an alternative approach, we used the share of physicians under 45 as an instrument. The effects remain consistent in sign, but the specification appears to suffer from a weak-IV problem. These results are shown in Appendix Tables D5, D6, D7, and D8.

[13] We implement the first-stage regression using city-level means for age groups and gender to mirror the granularity of our endogenous variable and the instruments as suggested by Duflo (2001).

5.2.2 Controlling for potentially omitted factors

A second concern for our identification strategy is the potential omission of variables that are correlated with the availability of reviews and drive a reduction in the care gap. To mitigate this concern, we added additional relevant control variables in columns 3-4 of Table 3. Specifically, we control for broadband internet usage, demographics (income, poverty, education), and the availability of physicians. After controlling for these variables, we observe that reviews still increase the likelihood of a follow-up visit (+4.7 p.p.) and reduce the time between visits (by 28.7 days).

We provide a more detailed description of this data, summary statistics, and regression results in Tables E1 and E2 of Appendix E. In Tables E3 and E4, we re-estimated our main specification from Table 3, but sequentially add potentially omitted control variables. As expected, we observe that the likelihood of a follow-up visit is negatively and significantly associated with income and poverty level, and internet adoption has a positive and significant effect, though its significance diminishes when all variables are controlled for jointly.

5.2.3 Placebo test: Patients of nonretiring physicians

Finally, we use a placebo test to rule out confounding factors that *generally* affect the time between visits. Such confounding factors should also affect patients of nonretiring physicians. Columns 7-8 of Table 3 replicate the regressions in columns 1-2 for patients of nonretiring physicians.[14]

Column 7 analyzes the probability of a follow-up visit within 15 months. In the placebo condition, this probability is estimated to *decrease* by 0.8% in treated cities. Column 8 analyzes the number of days until a patient's next visit to a physician with the same specialty. The coefficient is 3.57 days and is not statistically significant, despite the larger sample size and increased statistical power. We conclude that the background tendency of seeing physicians more frequently in treated cities is negligible.

In Appendix F we verify the consistency and robustness of our results. First, Appendix Tables F1 and F2 show the decomposition of the placebo effect by specialty, age, and city population growth. Second, we ensure that the placebo results are not driven by how we impose placebo retirement dates by using a patient's average time between visits over the full period of observation as dependent variable (see Appendix Table F3).

[14] We identify patients seeing nonretiring physicians in the same way as for retiring physicians. We randomly imposed placebo retirement dates on active physicians, evaluated whether their patients followed up with another visit within 15 months, and calculated the time between visits if they did.

5.2.4 Remaining limitations

These three robustness analyses together reduce various identification concerns. First, the IV approach rules out that selection into treatment (review generation) is driven by any physician-specific developments. Second, the additional controls account for other internet-driven factors (broadband) and important demographic developments. Third, the placebo test highlights that the pattern of a reduction in the care gap is not generally observed in treated cities, but only for patients whose relationship ended. We show the absence of a pre-trend and, by design, always control for time-invariant factors. Moreover, we always control for age-specific factors and show in a robustness check that the pattern is driven by dynamic places with higher population growth.

Any remaining confounding factors that drive the effects we observe would have to be (1) different from the ones we controlled for and (2) limited only to patients of retiring physicians, rather than all patients in a treated city. However, we cannot address one remaining source of bias. Adoption of online reviews is stronger in dynamic places with a younger population, and our effects are strongest in places where reviews are widely used and weakest where adoption is low. In other words, we estimate a (highly relevant) *average treatment effect on the treated* (ATT). However, this issue would disappear once review platforms are widely adopted everywhere. Until then, the concern merely confirms the need to encourage greater availability and adoption of online reviews of physicians by designing an engaging and comprehensive review platform.

6 Conclusion

Summary. We show that online reviews help patients to find a new physician when they need one. We use physicians' retirements as a disruptive shock that requires patients to find a new physician. We employ a DiD strategy in which we compare cities with and without many online reviews in the years of 2008 and 2017. When online reviews are available, patients are 7 p.p. more likely to follow up with their care within 15 months. Furthermore, if a patient follows up with a new physician, the time until this visit is on average about one month (30.7 days) shorter than otherwise.

Interpretation. Our findings highlight the potential of online reviews to improve efficiency and welfare when patients need to find a new physician. Patients consider online reviews when searching for a physician and these reviews affect patients' behavior. Online reviews seem to "make it easier" to visit a physician, and to reduce the risk of a gap in care whenever physician-patient relationships are interrupted. Societies or large health-care systems where information about good physicians is "implicit knowledge" might be able to harness online reviews to achieve more equity in health care by making access to information easier and more widespread.

Implications. Given their value to patients, health insurers, whether public or private, should pay close attention to online health-related reviews. Moreover, they should try to make the information on existing platforms more accessible to their clients, and consider providing carefully designed and incentive-compatible platforms that motivate patients to provide informative and accurate online reviews about physicians.

Further research. By showing that online reviews help to reduce the risk of interruptions to continuous care when physicians retire, we provide a first step to understanding the potential of online reviews to directly benefit patients. However, we believe that the same mechanism applies to many other life changes, especially for patients - for example, when they move to a new city (or even to a new neighborhood), need to see a new specialist, or change their insurance carrier. Further research should explore these other potential causes of interruptions in care. A second fruitful avenue for further research is studying patient-physician matches. We hypothesize that online reviews help patients to find better matches, and this could be tested by analyzing the number of physicians visited by patients before they commit to a particular one. Third, a long-term study could leverage the ongoing COVID pandemic to evaluate the risk of care gaps to patients' health. Such a study could determine the long-term health risks associated with a gap in care when treating cardiovascular disease or other serious chronic conditions.

References

Amaral-Garcia, Sofia, Mattia Nardotto, Carol Propper, and Tommaso Valletti, "Mums Go Online: Is the Internet Changing the Demand for Healthcare?," *Review of Economics and Statistics*, forthcoming.

Barach, Paul, Stacy D. Fisher, M. Jacob Adams, Gale R. Burstein, Patrick D. Brophy, Dennis Z. Kuo, and Steven E. Lipshultz, "Disruption of healthcare: Will the COVID pandemic worsen non-COVID outcomes and disease outbreaks?," dec 2020.

Bensnes, Simon and Ingrid Huitfeldt, "Rumor has it: How do patients respond to patient-generated physician ratings?," *Journal of Health Economics*, 2021, *76*, 102415.

Billari, Francesco C, Osea Giuntella, and Luca Stella, "Does broadband Internet affect fertility?," *Population studies*, 2019, *73* (3), 297–316.

Cabral, Luis and Ali Hortacsu, "The dynamics of seller reputation: Evidence from eBay," *The Journal of Industrial Economics*, 2010, *58* (1), 54–78.

Chen, Yiwei and Stephanie Lee, "User-Generated Physician Ratings and Their Effects on Patients' Physician Choices: Evidence from Yelp," *SSRN Discussion Paper*, 2021.

Chevalier, Judith A and Dina Mayzlin, "The effect of word of mouth on sales: Online book reviews," *Journal of Marketing Research*, 2006, *43* (3), 345–354.

Choi, Angela Aerry, Daegon Cho, Dobin Yim, Jae Yun Moon, and Wonseok Oh, "When seeing helps believing: The interactive effects of previews and reviews on e-book purchases," *Information Systems Research*, dec 2019, *30* (4), 1164–1183.

Darby, Michael R and Edi Karni, "Free competition and the optimal amount of fraud," *The Journal of Law and Economics*, 1973, *16* (1), 67–88.

Duan, Wenjing, Bin Gu, and Andrew B Whinston, "Do online reviews matter?—An empirical investigation of panel data," *Decision support systems*, 2008, *45* (4), 1007–1016.

Duflo, Esther, "Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment," *American economic review*, 2001, *91* (4), 795–813.

Emmert, Martin and Florian Meier, "An analysis of online evaluations on a physician rating website: evidence from a German public reporting instrument," *Journal of medical Internet research*, 2013, *15* (8), e157.

Forman, Chris, Anindya Ghose, and Batia Wiesenfeld, "Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets," *Information systems research*, 2008, *19* (3), 291–313.

Gao, Guodong Gordon, Jeffrey S McCullough, Ritu Agarwal, and Ashish K Jha, "A changing landscape of physician quality reporting: analysis of patients' online ratings of their physicians over a 5-year period," *Journal of medical Internet research*, 2012, *14* (1), e38.

Greaves, Felix, Utz J Pape, Dominic King, Ara Darzi, Azeem Majeed, Robert M Wachter, and Christopher Millett, "Associations between web-based patient ratings and objective measures of hospital quality," *Archives of internal medicine*, 2012, *172* (5), 435–436.

Hackl, Franz, Michael Hummer, and Gerald J. Pruckner, "Old boys' network in general practitioners' referral behavior?," *Journal of Health Economics*, sep 2015, *43*, 56–73.

Helmers, Christian, Pramila Krishnan, and Manasa Patnam, "Attention and saliency on the internet: Evidence from an online recommendation system," *Journal of Economic Behavior & Organization*, 2019, *161*, 216–242.

Holliday, Alison M., Allen Kachalia, Gregg S. Meyer, and Thomas D. Sequist, "Physician and Patient Views on Public Physician Rating Websites: A Cross-Sectional Study," *Journal of General Internal Medicine*, jun 2017, *32* (6), 626–631.

Howard, Paul, Senior Fellow, and Yevgeniy Feyman, "Yelp for health using the wisdom of crowds to find high-quality hospitals," 2017.

Hu, Nan, Paul A Pavlou, and Jennifer Zhang, "Can online reviews reveal a product's true quality? Empirical findings and analytical modeling of online word-of-mouth communication," in "Proceedings of the 7th ACM conference on Electronic commerce" 2006, pp. 324–330.

Kaye, Aaron, "Digitizing Doctor Demand: The Impact of Online Reviews in the Market for Primary Care Services," in "9th Annual Conference of the American Society of Health Economists" ASHECON 2020.

Lam, Kenneth, Cameron G Arnold, Rachel D Savage, Nathan M Stall, Lynn Zhu, Wei Wu, Katrina Piggott, Susan E Bronskill, and Paula A Rochon, "Does physician retirement affect patients? A systematic review," *Journal of the American Geriatrics Society*, 2020, *68* (3), 641–649.

Lu, Susan F and Huaxia Rui, "Can we trust online physician ratings? Evidence from cardiac surgeons in Florida," *Management Science*, 2018, *64* (6), 2557–2573.

Lu, Wei and Hong Wu, "How online reviews and services affect physician outpatient visits: content analysis of evidence from two online health care communities," *JMIR medical informatics*, 2019, *7* (4), e16185.

Luca, Michael, "Reviews, reputation, and revenue: The case of Yelp. com (No. 12-016)," *Harvard Business School*, 2011.

_ **and Sonal Vats**, "Digitizing doctor demand: The impact of online reviews on doctor choice," 2014.

Reimers, Imke C and Joel Waldfogel, "Digitization and pre-purchase information: the causal and welfare impacts of reviews and crowd ratings," *American Economic Review*, forthcoming.

Sabety, Adrienne H., Anupam B. Jena, and Michael L. Barnett, "Changes in Health Care Use and Outcomes after Turnover in Primary Care," *JAMA Internal Medicine*, feb 2021, *181* (2), 186–194.

Sahoo, Nachiketa, Chrysanthos Dellarocas, and Shuba Srinivasan, "The impact of online product reviews on product returns," *Information Systems Research*, sep 2018, *29* (3), 723–738.

Saifee, Danish H, Zhiqiang Zheng, Indranil R Bardhan, and Atanu Lahiri, "Are Online Reviews of Physicians Reliable Indicators of Clinical Outcomes? A Focus on Chronic Disease Management," *Information Systems Research*, 2020, *31* (4), 1282–1300.

Samuelson, William and Richard Zeckhauser, "Status quo bias in decision making," *Journal of risk and uncertainty*, 1988, *1* (1), 7–59.

Tu, Ha T and Johanna R Lauer, *Word of mouth and physician referrals still drive health care provider choice*, Center for Studying Health System Change Washington, DC, 2008.

Xu, Yuqian, Mor Armony, and Anindya Ghose, "The Interplay Between Online Reviews and Physician Demand: An Empirical Investigation," *Management Science*, 2021.

Yin, Dezhi, Sabyasachi Mitra, and Han Zhang, "When do consumers value positive vs. negative reviews? An empirical investigation of confirmation bias in online word of mouth," *Information Systems Research*, mar 2016, *27* (1), 131–144.

Online Appendix for *Healthy reviews? The impact of online physician ratings on healthcare outcomes*

Table of Contents

A Sample information

A.1 Data preparation details

Table A1: Raw counts of patients and claims found in the CDM during the pre- and post-treatment periods.

Pre Window: 2007Q1 - 2010Q4	Claims	Patients
Patient History Runway (15 months)	≈ 372 million	≈ 13.87 million
Retirements Detection Window (18 months)	≈ 504 million	≈ 15.08 million
Follow-Up Observation Window (15 months)	≈ 441 million	≈ 13.60 million
Total	≈ 1.32 billion	≈ 23.57 million
Post Window: 2014Q1 - 2017Q4	**Claims**	**Patients**
Patient History Runway (15 months)	≈ 515 million	≈ 14.14 million
Retirements Detection Window (18 months)	≈ 724 million	≈ 16.48 million
Follow-Up Observation Window (15 months)	≈ 732 million	≈ 17.27 million
Total	≈ 1.97 billion	≈ 26.56 million

NOTES: This table shows the prevalence of claims and patients in the CDM for the pre- and post-treatment periods. Each time period consists of 18 months to identify retirements, surrounded by 15 months both before and after to collect a more complete patient history.

Claims data. The pattern of patient visits was identified using health insurance claims data during two time periods corresponding to pre and post aggregation of per capita reviews. Each city was classified as accumulating either "high" or "low" number of per capita reviews. Optum's Clinformatics Data Mart (CDM) provides a complete picture of included patients' healthcare from 2007-2018. Importantly, the CDM includes information on patient geography in the form of zip code. Two periods of insurance claims were isolated for patients in a zip code in any of the 60 cities selected based on the online review data. During the first of these periods, we scanned for physician retirements from April 2008 to September 2009, when the number of online reviews per capita remained low in both the treatment and control groups. Alternatively, during the second period, we scanned for physician retirements from April 2015 to September 2016, when cities in the treatment group had a much high number of online reviews per capita than cities in the control group. Physicians that saw 20 or fewer distinct patients in a given period were excluded due to low volume. Physicians that saw patients in multiple zip codes were attributed to the zip code where the greatest share of their patients resided, unless that share was less than two thirds, in which case the physician was excluded.

In order to observe the effect of online reviews on a patients' search for a new physician, it is necessary to identify scenarios where a patient will be searching for a new physician with high probability. To accomplish this, physicians were observed over 18 months to detect a consistent pattern of activity lasting at least 3 months followed by an abrupt halt to activity that lasted until the end of the observation period. A physician's activity is determined using two metrics calculated at the physician-month level: number of distinct patients seen and number of claims filed in a given month.We explored using criteria other than patient and claim volumes for identifying physician retirements when creating the data set. These include the use of patient volume alone, claim volume alone, total charges (in dollars), and patients, claims and charges in combination. The results for the various retirement criteria are largely the same as the main results and available upon request. Once retirement dates were determined, patients of retiring physicians were monitored for an additional 15 months before and after the retirement detection window in order to gain a more full picture of a given patient's visiting behavior and avoid data censoring. Table A1 shows the volume of claims as well as a count of distinct patients for each period of our analysis. While it is not possible to determine if physicians are indeed "retiring", it is clear they are not providing services for their former patients. It is possible, for instance, that a given physician is no longer considered "within network". Regardless of reason, these patients will consequently be forced to find a new physician in the same specialty. The physician retirements detected are summarized in Figure 1 separated by city and labeled by treatment group. After physician retirements were identified, patient-physician relationships were constructed subject to additional filters on where visits took place (office or outpatient hospital) and what services were rendered (services coded as evaluation & management) to avoid unplanned visits and hospitalizations.

Online reviews Reviews of physicians on the Yelp platform were collected as of August 2018. Reviews were collected across the top 100 most populous cities in the United States according to estimates from the 2014-2018 American Community Survey provided by the US Census Bureau. Furthermore, individual physicians were identified by Yelp's search algorithm using only city, state, and specialty as inputs. The entire history of reviews was captured for physicians in each city across the specialities of cardiology, gastroenterology, addiction medicine, psychology, dermatology, and infectious disease. This resulted in 165,944 reviews across 11,077 physicians, with the earliest review dating back to October 2004. The number of reviews per capita were calculated for each city over time and cities were classified as either "high" or "low" based on the number of reviews per capita in 2018, at the end of the observation window. The number of per capita reviews remained close to 0 for all cities until the mid-late 2000s, which will serve as a pre-treatment period. We initially selected 60 cities, with 30 cities accumulating a high number of reviews per capita, and 30 accumulating almost no reviews per capita. Finally, cities were labelled as treated if they ended up with 200+ reviews per 100,000 people in 2017, or had over 150 specialists with multiple reviews. Figure 1 displays the pattern of review accumulation for each city, separated by treatment group.

A.2 Reviews by city - Summary

Table A2: Cities with lowest number of review intensity and treatment categorization

	treat	loc	rev_per_cap	n_rev	n_doc	twoplus
1	Control	Laredo	2.541	6	5	1
2	Control	Fort+Wayne	4.730	12	5	3
3	Control	Corpus+Christi	6.553	20	11	5
4	Control	Wichita	9.677	37	19	11
5	Control	El+Paso	10.322	67	26	15
6	Control	Lincoln	11.224	29	14	8
7	Control	Madison	13.293	31	11	7
8	Control	Tulsa	13.779	54	24	11
9	Control	Lexington	13.861	41	14	7
10	Control	Toledo	14.624	42	19	12
11	Control	Greensboro	15.204	41	15	11
12	Control	Oklahoma+City	18.276	106	40	21
13	Control	Milwaukee	18.997	113	52	23
14	Control	Lubbock	22.215	51	14	7
15	Control	Anchorage	22.274	65	20	12
16	Control	Baton+Rouge	23.094	53	25	12
17	Control	Winston-Salem	23.517	54	23	10
18	Control	Louisville	23.940	143	52	27
19	Neither	Rochester	24.695	52	26	8
20	Control	Albuquerque	25.282	138	33	17
21	Control	Omaha	25.920	106	27	19
22	Control	Colorado+Springs	27.136	113	31	22
23	Control	Indianapolis	27.668	227	68	39
24	Control	Memphis	31.226	202	59	35
25	Control	Spokane	32.070	67	19	7
26	Control	Jacksonville	35.532	292	89	54
27	Control	Cleveland	35.533	141	49	24
28	Neither	Columbus	35.577	280	70	44
29	Control	Buffalo	36.738	96	34	20
30	Control	Pittsburgh	42.198	129	55	29
31	Control	San+Antonio	45.201	600	118	77
32	Neither	Fort+Worth	47.355	351	86	61
33	Neither	Kansas+City	50.458	232	66	37
34	Neither	Charlotte	52.500	384	72	44
35	Neither	Baltimore	56.042	348	66	50
36	Neither	Birmingham	59.839	127	42	19
37	Neither	St.+Louis	63.891	204	87	39
38	Neither	Cincinnati	64.996	193	50	31
39	Neither	Virginia+Beach	67.809	297	68	43
40	Neither	Nashville	71.188	428	99	58
41	Neither	Bakersfield	79.428	276	43	27
42	Neither	Norfolk	80.724	196	43	32
43	Neither	New+Orleans	87.834	302	73	38
44	Neither	Arlington	89.755	328	58	41
45	Neither	Saint+Paul	92.259	263	41	27
46	Neither	Detroit	93.306	666	184	108
47	Neither	Fresno	97.238	481	69	50
48	Neither	Tucson	100.170	521	85	49
49	Neither	Minneapolis	116.839	447	82	60
50	Neither	Boston	117.391	725	98	75

Table A3: Cities with highest number of review intensity and treatment categorization

	treat	loc	rev_per_cap	n_rev	n_doc	twoplus
1	Neither	Chesapeake	126.007	280	66	43
2	Neither	St.+Petersburg	126.650	310	85	56
3	Neither	Raleigh	148.802	601	113	72
4	Neither	Stockton	159.407	465	91	55
5	Neither	Reno	161.619	364	53	36
6	Neither	Portland	168.044	981	124	89
7	Neither	Newark	177.528	492	63	43
8	Neither	New+York	59.852	4,893	599	420
9	Neither	Philadelphia	77.981	1,190	249	161
10	Neither	Houston	100.035	2,101	329	228
11	Neither	Chicago	159.408	4,297	415	297
12	Neither	Dallas	181.497	2,174	356	240
13	Neither	San+Bernardino	210.076	441	58	46
14	Neither	Tampa	213.280	716	208	131
15	Neither	Durham	261.464	597	113	73
16	Neither	Denver	268.263	1,610	196	142
17	Treatment	Phoenix	282.575	4,085	405	291
18	Treatment	Honolulu	321.121	1,083	133	93
19	Treatment	San+Diego	332.950	4,353	399	302
20	Treatment	Orlando	345.363	823	175	129
21	Treatment	Sacramento	391.007	1,824	175	123
22	Treatment	Seattle	403.345	2,455	260	197
23	Treatment	Austin	419.919	3,319	247	195
24	Treatment	Plano	436.036	1,133	183	124
25	Treatment	Atlanta	436.425	1,833	295	210
26	Treatment	Garland	507.766	1,152	203	129
27	Treatment	Las+Vegas	509.631	2,975	211	165
28	Treatment	Aurora	524.490	1,705	180	129
29	Treatment	Los+Angeles	531.585	20,161	1,093	943
30	Treatment	Irving	546.951	1,183	190	122
31	Neither	Washington	575.514	3,463	297	213
32	Treatment	San+Jose	593.588	5,615	477	374
33	Treatment	Miami	636.114	2,541	348	238
34	Treatment	San+Francisco	761.517	6,132	432	338
35	Treatment	Mesa	771.682	3,388	298	223
36	Treatment	Chandler	801.701	1,893	159	122
37	Treatment	Chula+Vista	903.180	2,203	197	147
38	Treatment	Santa+Ana	940.751	3,053	192	162
39	Treatment	North+Las+Vegas	978.978	2,124	153	118
40	Treatment	Hialeah	992.571	2,230	307	209
41	Treatment	Jersey+City	1,060.191	2,625	337	250
42	Treatment	Fremont	1,093.470	2,341	187	151
43	Treatment	Long+Beach	1,101.768	5,093	335	281
44	Treatment	Henderson	1,128.317	2,908	214	166
45	Neither	Riverside	1,192.282	3,623	280	228
46	Treatment	Oakland	1,546.616	6,043	412	327
47	Neither	Glendale	1,563.596	3,545	350	247
48	Treatment	Scottsdale	1,900.775	4,132	417	300
49	Treatment	Irvine	3,657.681	7,768	491	409
50	Treatment	Anaheim	4,594.888	15,451	1,065	904

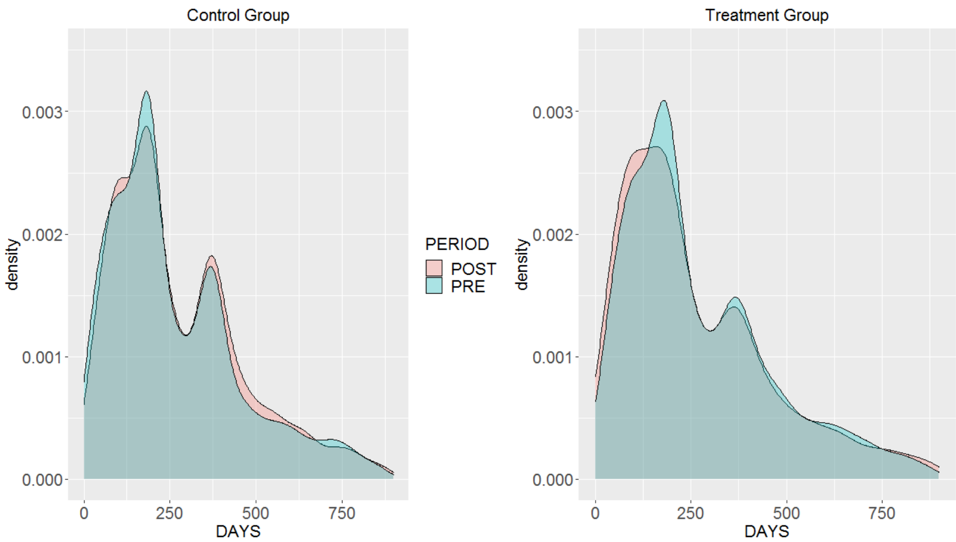
A.3 Summary statistics by treatment and period

Table A4: Overview of the sample means by treatment status.

	Overall	Pre-Control	Pre-Treat	Post-Control	Post-Treat
fup15mo	0.398	0.445	0.353	0.435	0.335
DAYS	275.316	271.711	274.181	282.175	268.480
infc_gast	0.146	0.229	0.124	0.101	0.131
derm	0.293	0.232	0.381	0.200	0.404
psych	0.029	0.001	0.013	0.056	0.061
card	0.532	0.539	0.483	0.643	0.404
AGE	64.732	68.178	62.654	67.830	56.709
TREAT	0.448	0	1	0	1
did	0.146	0	0	0	1
post	0.436	0	0	1	1
female	0.548	0.538	0.550	0.547	0.566
age_u20	0.031	0.014	0.050	0.011	0.061
age_2039	0.090	0.051	0.106	0.055	0.194
age_4049	0.066	0.047	0.073	0.053	0.114
age_5064	0.172	0.157	0.157	0.194	0.189
age_6574	0.272	0.303	0.249	0.314	0.180
age_75u	0.369	0.427	0.365	0.374	0.262

NOTES: This table shows the sample means by treatment status.The sample sizes are 7080 observations in “pre-control”, 7873 in “post-control,” 8,206 “pre-treatment,” and 3,954 in the “post-treatment” group.

Figure A1: Time between visits after a physician retirement.



NOTES: The figures show the distribution of the time between visits for patients after a physician's retirement. The left-hand figure shows this distribution for cities in the control group, whereas the right-hand figure shows the distribution for cities in the treatment group. Each figure compares the distribution before reviews were available (blue) to the distribution after reviews were available in cities in the treatment group (red).

A.4 Test of the care gap's statistical significance

Table A5: Welch two sample t-tests: Inter-visit Times

	Non-Ret Mean	Before Ret Mean	After Ret Mean	p-value
	137.75	125.017		$< .0001$
	137.75		275.316	$< .0001$
		125.017	275.316	$< .0001$
N Obs	173,216	18,897	13,007	

NOTES: This table shows the average inter-visit time for patients. Column 1 shows the average inter-visit times leading up the a placebo retirement date. Column 2 is the average inter-visit time before an actual retirement. The third column shows the mean inter-visit time *immediately* following a retirement. Column 4 confirms pair-wise that the average inter-visit time between these three groups differs significantly.

The key takeaway from Appendix Table A5 is that the time between visits following a physician retirement is much higher than the mean of the times between visits both before retirement and for patients of nonretiring physicians. The number of observations in the first column of Table A5 represent the number of patients of nonretiring physicians that had at least two visits prior to a placebo retirement date, allowing us to calculate the mean time between visits for a particular patient & specialty. Accordingly, Appendix Table F3 is built upon the same sub sample. The observations in the second column of Appendix Table A5 represent patients of retiring physicians with at least two visits prior to their physician's retirement date, which allows us to calculate their mean time between visits. The third column of Appendix Table A5 represents patients that visited a new physician after theirs retired, and corresponds to the same sub-sample as found in columns (7), and (8) of Table 3.

A.5 Tests for the Parallel Trends Assumption

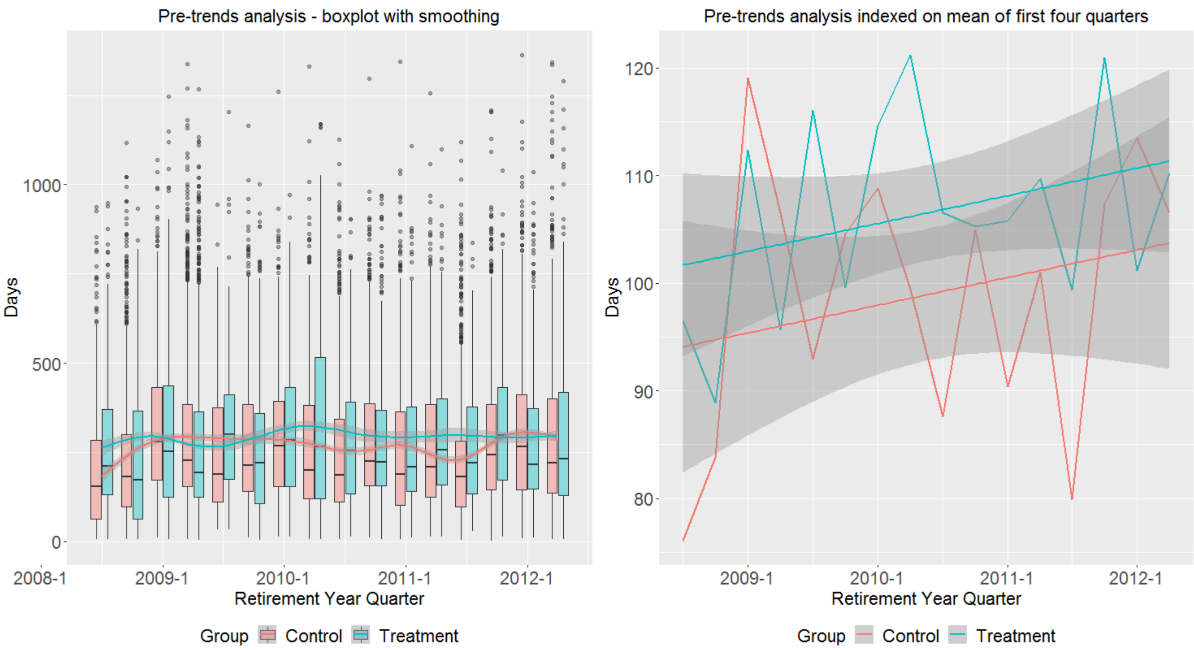
Our DiD estimation approach requires verification of whether the parallel trends assumption is satisfied. Figure A2 gives a visual analysis of the pre-treatment trends in the data. The left-hand figure compares the quarterly averages of the time between visits after a retirement in treated and untreated cities. We provide this comparison for the year used in our pre-treatment period (2008Q2 to 2009Q1) and the subsequent three years. The right-hand panel applies linear smoothing to the data and shows the corresponding confidence intervals. The figures suggest that the time between visits tends to be slightly longer on average in treated cities. There is slightly faster growth in the time between visits after retirements in cities that receive treatment by reviews, but the difference is small and not statistically significant. The visual impression is confirmed by a regression that analyzes the interaction of the treatment dummy with a time trend (or retirement quarters), shown in Appendix Table A6. Although the time between visits is not the same for the treated and untreated groups, there is no statistically significant difference in how the time between visits develops over time.

Table A6: Robustness Check: Pre-trend Analysis.

	Dependent variable: Inter-visit times.			
	Linear		Non-Parametric	
	(1)	(2)	(3)	(4)
Time trend		2.513***		
		(0.385)		
Treated X Time trend	0.781	0.413		
	(0.707)	(0.679)		
Treated X 2009q3			26.292	65.702***
			(24.507)	(18.469)
Treated X 2009q4			2.267	6.974
			(18.758)	(16.183)
Treated X 2010q1			12.225	4.693
			(15.206)	(11.272)
Treated X 2010q2			52.297***	51.958***
			(13.680)	(11.038)
Treated X 2010q3			24.586	37.995*
			(21.042)	(19.986)
Treated X 2010q4			4.271	20.413
			(15.256)	(13.206)
Treated X 2011q1			61.548***	28.543*
			(16.762)	(14.935)
Treated X 2011q2			−1.048	12.259
			(16.328)	(13.375)
Treated X 2011q3			17.074	15.481
			(22.504)	(21.402)
Treated X 2011q4			4.600	36.644**
			(18.570)	(17.378)
Treated X 2012q1			−10.623	16.208*
			(12.074)	(9.667)
Treated X 2012q2			32.262***	49.387***
			(12.003)	(10.140)
Treated X 1st quarter				9.085*
				(5.184)
Treated X 2nd quarter				−6.247
				(4.717)
Treated X 3rd quarter				−49.306***
				(5.484)
Patient Char.	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes
Retirement YQ FE	Yes	No	Yes	No
City FE	Yes	Yes	Yes	Yes
Observations	20,896	20,896	20,896	20,896
R^2	0.066	0.057	0.068	0.063
Adjusted R^2	0.063	0.054	0.064	0.059

NOTES: In this table we analyze whether a patient's inter-visit time after their physician's retirement evolves similarly for patients in cities with and without reviews. In cols. 1 and 2 we control for a linear time trend, In cols. 3 and 4 we interact quarterly indicator with the treatment indicator. Standard errors in parenthesis. Significance levels: *p<0.1; **p<0.05; ***p<0.01

Figure A2: Pre-treatment Trends.



NOTES: In this figure we analyze whether a patient's time between visits after their physician retires evolves similarly over time for patients in cities with and without reviews. The left figure shows quarterly box plots of the distribution of these patients' time between visits by treatment and control groups. The right figure shows the linear trend of the average time between visits per patient, indexed by the average time between visits during the first four quarters (our pre-period).

B Alternative sample, specification and variable definitions

B.1 Sample: Pre-treatment time-window

Our time window for the pre-treatment period ranges from 2007 to 2010. In this subsection, we also report the respective analyses using a different time window for the pre-treatment period. Specifically, we examine the effect on follow-up probability in Table B1, and the effect on inter-visit times in Table B2. Results do not change qualitatively, with the exception of the effect on follow-up probability becoming insignificant in the latest of the pre-treatment periods (with retirements spanning 2011-2012). This is expected, as the associated difference in treatment effect gets smaller when moving closer in time to the post-treatment period.

Table B1: Main results for probability of patient follow-up under alternative pre-treatment periods.

	Dependent variable:			
	fup15mo			
	(1)	(2)	(3)	(4)
age_u20	0.002	0.040**	0.052**	0.033
	(0.018)	(0.018)	(0.021)	(0.021)
age_5064	0.089***	0.065***	0.059***	0.077***
	(0.010)	(0.010)	(0.011)	(0.011)
age_6574	0.182***	0.161***	0.140***	0.174***
	(0.011)	(0.011)	(0.012)	(0.011)
age_75u	0.204***	0.180***	0.154***	0.192***
	(0.011)	(0.011)	(0.011)	(0.011)
male	0.019***	0.014**	0.023***	0.026***
	(0.006)	(0.006)	(0.006)	(0.006)
post	−0.057***	0.018*	−0.016*	0.033***
	(0.009)	(0.009)	(0.009)	(0.008)
DiD	0.070***	0.085***	0.128***	−0.010
	(0.014)	(0.014)	(0.015)	(0.015)
Ref Category	20-49	20-49	20-49	20-49
Specialty FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	27,113	21,063	21,615	24,868

NOTES: In this table we estimate model 1 of Table B6 using different non-overlapping and adjacent pre-treatment retirement detection periods. Column (1) represents the same pre-treatment retirement detection period as throughout the article (2008-2009). Columns (2), (3), and (4) span over 2009-2010, 2010-2011, and 2011-2012, respectively. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

Table B2: Main results for time between visits under alternative pre-treatment periods.

	Dependent variable:			
	DAYS			
	(1)	(2)	(3)	(4)
age_u20	−24.750	−32.352*	−55.159***	−29.810
	(15.522)	(17.692)	(17.273)	(18.342)
age_5064	−2.097	−9.669	10.104	−0.583
	(7.989)	(8.783)	(8.754)	(8.717)
age_6574	−8.664	−10.816	−1.336	−5.116
	(7.843)	(8.893)	(8.669)	(8.575)
age_75u	−9.931	−12.558	−4.626	−13.122
	(7.751)	(8.836)	(8.601)	(8.557)
male	−10.349***	−8.618**	−12.032***	−12.722***
	(3.505)	(4.309)	(3.943)	(3.677)
post	24.943***	14.832**	18.497***	2.092
	(5.376)	(6.158)	(5.336)	(5.033)
DiD	−30.685***	−50.037***	−53.463***	−38.731***
	(9.131)	(10.556)	(10.283)	(10.056)
Ref Category	20-49	20-49	20-49	20-49
Specialty FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	13,007	8,848	10,061	12,102

NOTES: In this table we estimate model 2 of Table B6 using different non-overlapping and adjacent pre-treatment retirement detection periods. Column (1) represents the same pre-treatment retirement detection period as throughout the article (2008-2009). Columns (2), (3), and (4) span over 2009-2010, 2010-2011, and 2011-2012, respectively. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

B.2 Specification: Different time fixed effects

In our main results in Table B6, we control for unobserved temporal heterogeneity in inter-visit times solely by our indicator variable "post", which identifies our treatment period. To rule out that our results are driven by compositional effects over time (e.g. more last visits in period of low physician demand in cities with reviews in the treatment period), we test the robustness of our findings by controlling for different types of time fixed effects. We consider various combinations of the physician retirement date and the date of a patient's last visit to their retiring physician. Tables B3 and B4 show column (1) and (4) as in Table B6, but with various combinations of time fixed effects. The results in Table B3 are primarily consistent with our main results in sign and significance. The results in Table B4 are consistent with the main results in sign, but the magnitude is smaller for some types of time fixed effect.

Table B3: Time FE comparison for following up within 15 months as dependent variable.

	Dependent variable:				
	fup15mo				
	None	PrevYq	PrevYr+PrevMo	RetYq	RetYr+RetMo
	(1)	(2)	(3)	(4)	(5)
age_u20	0.002	0.021	0.019	-0.017	-0.013
	(0.018)	(0.017)	(0.017)	(0.018)	(0.018)
age_5064	0.089***	0.082***	0.081***	0.088***	0.089***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
age_6574	0.182***	0.167***	0.166***	0.180***	0.179***
	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
age_75u	0.204***	0.186***	0.186***	0.201***	0.200***
	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
male	0.019***	0.014**	0.014**	0.019***	0.019***
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
post	-0.057***				
	(0.009)				
DiD	0.070***	0.064***	0.063***	0.053***	0.044***
	(0.014)	(0.013)	(0.013)	(0.014)	(0.015)
Ref Category	20-49	20-49	20-49	20-49	20-49
Patient Char.	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes
Time FE	None	PrevYq	PrevYr+PrevMo	RetYq	RetYr+RetMo
City FE	Yes	Yes	Yes	Yes	Yes
Observations	27,113	27,113	27,113	27,113	27,113

NOTES: In this table we estimate specification (1) of Table B6 using different alternative combinations of fixed effects. Col 1 is the same as in the main result, Col 2 applies controls for the quarter of the previous visit. Col 3 includes dummies for the year and the month of the previous visit, Col 4 includes a fixed effect for the retirement quarter, and Col 5 controls has dummies for the month and the year of the retirement. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

Table B4: Time FE comparison with time between visits as the dependent variable.

	Dependent variable:				
	DAYS				
	None	PrevYq	PrevYr+PrevMo	RetYq	RetYr+RetMo
	(1)	(2)	(3)	(4)	(5)
age_u20	−24.750	−36.179***	−38.081***	−17.554	−18.277
	(15.522)	(13.040)	(12.990)	(15.494)	(15.459)
age_5064	−2.097	−0.783	−2.480	−1.187	−2.620
	(7.989)	(6.712)	(6.694)	(7.967)	(7.958)
age_6574	−8.664	−2.948	−5.737	−9.216	−10.019
	(7.843)	(6.591)	(6.574)	(7.841)	(7.861)
age_75u	−9.931	−3.673	−6.109	−10.219	−11.810
	(7.751)	(6.514)	(6.496)	(7.759)	(7.785)
male	−10.349***	−4.756	−4.710	−10.808***	−10.666***
	(3.505)	(2.946)	(2.934)	(3.495)	(3.485)
post	24.943***				
	(5.376)				
DiD	−30.685***	−46.290***	−44.911***	−19.458**	−6.954
	(9.131)	(7.702)	(7.671)	(9.412)	(9.498)
Ref Category	20-49	20-49	20-49	20-49	20-49
Patient Char.	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes
Time FE	None	PrevYq	PrevYr+PrevMo	RetYq	RetYr+RetMo
City FE	Yes	Yes	Yes	Yes	Yes
Observations	13,007	13,007	13,007	13,007	13,007

NOTES: In this table we estimate specification (4) of Table B6 using different alternative combinations of fixed effects. Col 1 is the same as in the main result, Col 2 applies controls for the quarter of the last visit before retirement. Col 3 includes dummies for the year and the month of the last visit before retirement, Col 4 includes a fixed effect for the retirement quarter, and Col 5 controls for the month and the year of the retirement. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

B.3 Variable definition: Follow-up timing

Our main results in Columns 1-3 of Table B6 are attained using a 15 month cut off when labelling a patient as having followed up or not. To test the robustness of our result, we explore the effect of using various other cut-off points in Table B5, including the 15 month specification used in the main results. The significance of the DiD term persists under all specifications. The largest effect is found for follow-up visits within 12 months, as shown in column (4). This is not surprising since a period of 12 months is the usual schedule for routine visits.

Table B5: Probability of following up within various time frames.

	Dependent variable:				
	3 Months	6 Months	9 Months	12 Months	15 Months
	(1)	(2)	(3)	(4)	(5)
age_u20	0.007	−0.028*	−0.041*	−0.062***	−0.089***
	(0.010)	(0.014)	(0.017)	(0.018)	(0.018)
age_2039	−0.015*	−0.053***	−0.063***	−0.086***	−0.107***
	(0.007)	(0.010)	(0.011)	(0.012)	(0.012)
age_4049	−0.013	−0.038***	−0.052***	−0.061***	−0.067***
	(0.007)	(0.010)	(0.012)	(0.013)	(0.013)
age_6574	0.015**	0.036***	0.076***	0.077***	0.094***
	(0.005)	(0.007)	(0.009)	(0.009)	(0.009)
age_75u	0.018***	0.059***	0.101***	0.102***	0.116***
	(0.005)	(0.007)	(0.008)	(0.009)	(0.009)
female	−0.002	−0.012**	−0.022***	−0.019***	−0.018**
	(0.003)	(0.005)	(0.005)	(0.006)	(0.006)
post	−0.031***	−0.047***	−0.059***	−0.065***	−0.057***
	(0.005)	(0.007)	(0.008)	(0.009)	(0.009)
DiD	0.032***	0.047***	0.068***	0.075***	0.070***
	(0.008)	(0.011)	(0.013)	(0.014)	(0.014)
Patient Char.	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Observations	27,113	27,113	27,113	27,113	27,113

NOTES: This table compares the main result with alternative time frames determining if a patient has followed-up or not: 3 months(Col 1), 6 months (Col 2), 9 months (Col 3), 12 months (Col 4), and the baseline of 15 months in Col 5. The effect is positive throughout, weaker for short intervals and peaks at 12 months. Standard errors in parenthesis: *p<0.05; **p<0.01; ***p<0.001

B.4 Additional result: Main effect by age and specialty

Table B6: Effect of reviews on follow-up visit (LPM) and time between visits.

	Dependent variable:					
	Follow-up visit (15m)			time between visits (days)		
	Base	Speciality	Patient	Base	Speciality	Patient
	(1)	(2)	(3)	(4)	(5)	(6)
age_u20	0.002	0.005	−0.012	−24.750	−27.267*	−36.695**
	(0.018)	(0.018)	(0.021)	(15.522)	(15.555)	(18.617)
age_5064	0.089***	0.088***	0.091***	−2.097	−0.877	−8.534
	(0.010)	(0.010)	(0.012)	(7.989)	(7.996)	(8.966)
age_6574	0.182***	0.181***	0.179***	−8.664	−6.554	−9.891
	(0.011)	(0.011)	(0.012)	(7.843)	(7.894)	(8.706)
age_75u	0.204***	0.202***	0.195***	−9.931	−7.681	−7.458
	(0.011)	(0.011)	(0.012)	(7.751)	(7.824)	(8.600)
male	0.019***	0.018***	0.021***	−10.349***	−10.344***	−11.227***
	(0.006)	(0.006)	(0.006)	(3.505)	(3.504)	(3.732)
post	−0.057***	−0.059***	−0.057***	24.943***	26.120***	25.194***
	(0.009)	(0.009)	(0.009)	(5.376)	(5.387)	(5.373)
DiD	0.070***	0.066***	0.057***	−30.685***	−32.509***	−34.376**
	(0.014)	(0.017)	(0.021)	(9.131)	(10.675)	(16.536)
DiD_derm		−0.018			10.955	
		(0.020)			(13.014)	
DiD_infc_gast		0.130***			−72.102***	
		(0.028)			(19.751)	
DiD_psych		0.033			28.685	
		(0.040)			(30.765)	
DiD_male			−0.017			8.006
			(0.016)			(10.779)
DiD_u20			0.052			37.984
			(0.039)			(33.662)
DiD_5064			−0.024			39.695**
			(0.025)			(19.301)
DiD_6574			0.007			7.073
			(0.026)			(18.678)
DiD_75u			0.071***			−29.672*
			(0.024)			(17.414)
Patient Char.	Yes	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,113	27,113	27,113	13,007	13,007	13,007

NOTES: In this table we analyze the effect of reviews on a patient's likelihood to follow up with a new physician (cols. 1-3) and the number of days until this follow-up visit occurs (cols. 4-6) after their old physician retires. Columns 1 and 4 show the baseline result (reference category: patients age 20-49 years). Columns 2 and 5 explore the heterogeneity of the treatment effect across specialty (reference: cardiology), and columns 3 and 6 by patient characteristics (reference: female patients age 20-49). Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01.

B.5 Separate analysis by specialties

In the main analysis, we pooled all patient observations regardless of the specialty of the treating physician. In this subsection, we also report the respective analyses using only the sub-sample of patients visiting a physician of a specific specialty. The results for the likelihood of follow-up can be found in Table B7, whereas the analysis on the time to follow-up can be found in Table B8. The analysis confirms the results in Tables B6 and shows that the effect is present in cardiology as well as for gastroenterologists and infectious disease specialists.

Table B7: Treatment effect on follow-up probability by speciality.

	Dependent variable:			
	fup15mo			
	Card	Derm	Psych	Other
	(1)	(2)	(3)	(4)
age_u20	0.053	0.001	0.026	-0.472^{***}
	(0.183)	(0.019)	(0.062)	(0.074)
age_5064	0.187^{***}	0.069^{***}	-0.005	0.009
	(0.021)	(0.015)	(0.040)	(0.019)
age_6574	0.303^{***}	0.111^{***}	-0.015	0.039^{*}
	(0.020)	(0.017)	(0.064)	(0.022)
age_75u	0.302^{***}	0.193^{***}	-0.033	0.072^{***}
	(0.019)	(0.018)	(0.081)	(0.023)
male	0.032^{***}	0.021^{**}	-0.049	-0.025^{*}
	(0.008)	(0.010)	(0.030)	(0.013)
post	-0.051^{***}	-0.012	-0.039	-0.031
	(0.012)	(0.024)	(0.199)	(0.021)
DiD	0.069^{***}	0.036	-0.186	0.212^{***}
	(0.021)	(0.030)	(0.242)	(0.074)
Ref Category	20-49	20-49	20-49	20-49
Patient Char.	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	14,433	7,937	791	3,952

NOTES: This table explores the main model on the probability of patient follow-up by speciality of retiring physician. Columns (1), (2), and (3) are determined by patients of retiring cardiologists, dermatologists, and psychiatrists, respectively. Column (4) is determined by patients of gastroenterologists and infectious disease specialists. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

Table B8: Treatment effect on follow-up time by speciality.

	Dependent variable:			
	DAYS			
	Card	Derm	Psych	Other
	(1)	(2)	(3)	(4)
age_u20	-210.964	-24.119	65.883	269.939*
	(186.477)	(18.404)	(56.820)	(163.474)
age_5064	-22.778	13.978	14.822	7.844
	(13.870)	(12.835)	(31.260)	(24.506)
age_6574	-30.112^{**}	20.358	11.961	23.669
	(13.212)	(14.325)	(44.220)	(24.819)
age_75u	-30.730^{**}	8.892	7.528	27.541
	(13.110)	(14.303)	(55.129)	(25.341)
male	-7.952^{**}	-17.693^{**}	20.569	-9.942
	(4.048)	(7.810)	(23.222)	(14.534)
post	15.590**	-11.134		-16.627
	(6.153)	(16.922)		(25.152)
DiD	-26.729^{**}	3.938	-9.068	248.058**
	(11.216)	(22.307)	(103.096)	(103.683)
Ref Category	20-49	20-49	20-49	20-49
Patient Char.	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	8,518	3,099	266	1,124

NOTES: This table explores the main model on patient inter-visit time by speciality of retiring physician. Columns (1), (2), and (3) are determined by patients of retiring cardiologists, dermatologists, and psychiatrists, respectively. Column (4) is determined by patients of gastroenterologists and infectious disease specialists. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

B.6 Additional result: The effect by city growth

In this subsection we document an additional result which distinguishes the treatment effect by city growth. For this, we have grouped patients in our sample into three categories based on whether they live in a city with low, medium, or high population growth over the years 2010 to 2017. Note that this distinction was made at the city level using the 33$^{\text{rd}}$ and 66$^{\text{th}}$ percentile of cities in our sample, ranked by population growth. This translates to different weights of each category at the patient level. In Table B9 we document that 58% of patients in our data set live in cities showing high population growth, 23% in cities showing medium growth, and 19% in cities with low growth.

Table B9: Descriptive statistics for city growth.

Variable name	Mean
High population growth (top 33%)	0.58
Medium population growth (middle 33%)	0.23
Low population growth (bottom 33%)	0.19

NOTES: The table shows the summary statistics of the main estimation sample used in Table B6. The number of observations is 27,113.

We exploit this information in the regression analyses of Table B10 in columns (2) and (4). The dependent variable in columns (1) & (2) indicates whether or not patients visited a physician in the same specialty of their retiring physician within 15 months of the retirement date. The dependent variable in columns (3) & (4) is the number of days between visits surrounding a physician's retirement. Columns 1 and 3 repeat the main results of Table B6.

In column (2) we observe the effect is driven by cities with high population growth, which is consistent with the idea that reviews are most useful in dynamic places that see a lot of change. It appears to be reversed in cities with low growth, where it seems to be easier for physicians to build a reputation through word of mouth. Column (4) also mirrors this result, showing that the reduction of the inter-visit duration is driven by patients in cities with high population growth.

Table B10: Regressions regarding city population growth.

	Dependent variable:			
	Follow-Up		DAYS	
	Base	Growth	Base	Growth
	(1)	(2)	(3)	(4)
age_u20	0.002	0.003	-24.750	-25.954^{*}
	(0.018)	(0.018)	(15.522)	(15.521)
age_5064	0.089^{***}	0.089^{***}	-2.097	-2.262
	(0.010)	(0.010)	(7.989)	(7.985)
age_6574	0.182^{***}	0.182^{***}	-8.664	-7.915
	(0.011)	(0.011)	(7.843)	(7.848)
age_75u	0.204^{***}	0.204^{***}	-9.931	-9.022
	(0.011)	(0.011)	(7.751)	(7.758)
male	0.019^{***}	0.019^{***}	-10.349^{***}	-10.372^{***}
	(0.006)	(0.006)	(3.505)	(3.503)
post	-0.057^{***}	-0.057^{***}	24.943^{***}	24.993^{***}
	(0.009)	(0.009)	(5.376)	(5.374)
DiD	0.070^{***}	0.091^{***}	-30.685^{***}	-39.774^{***}
	(0.014)	(0.015)	(9.131)	(9.447)
DiD_lowgrwth		-0.339^{***}		86.936^{**}
		(0.053)		(42.850)
DiD_medgrwth		-0.066^{*}		92.304^{***}
		(0.038)		(28.614)
Ref Category	20-49	DiD×H.G.	20-49	DiD×H.G.
Patient Char.	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	27,113	27,113	13,007	13,007

NOTES: This table analyzes whether or not patients visited a physician in the same specialty of their retiring physician within 15 months of the retirement date (Columns 1-2) and the number of days to the next visit after a retirement (Columns 3-4). Columns 1 and 3 shows the base results as in the main results of Table B6. Columns 2 and 4 explore the heterogeneity of the treatment effect across city population growth. Standard errors in parenthesis: *p<0.05, **p<0.01, ***p<0.001.

C Detailed discussion of potential identification issues

The key challenge in our analysis is identifying whether a causal link exists between the presence of online physician reviews and the time needed for patients to select their new physicians. In what follows, we discuss the main hindrances to identification and how we address them.

Reverse causality. The first concern is that a shorter care-gap drives the creation of reviews in treated cities. We consider this scenario unlikely for the following reasons. First, we use reviews prior to retirement, that is, reviews created before 2018, when our claims data in the treatment period start. Second, the patients who post reviews and those who benefit from them are not the same. This implies that the availability of reviews could be exogenous to the patient's search. Third, patients of retired physicians are only a small share of patients overall. Therefore, it is unlikely that these patients drive the creation of reviews.

Measurement error. Another concern might arise from measurement error. Although we correctly and precisely measure the availability of reviews in each city, in our claims data set, we do not observe whether physician reviews are visible to the patients, and if so, which ones. This could result in attenuation bias. Although, because of anonymity requirements, this concern can not be mitigated from a data perspective, we believe that the risk of this kind of bias is also rather small. First, although we cannot observe whether our patients have read reviews about the specific physician they end up with, it could well be that they have used reviews to eliminate options from their consideration set. Second, even if it was not the patients themselves who used reviews, they might have helped to make a more informed decision if the patients were helped by a relative or friend. For example, although older patients might not use reviews directly, they could still benefit from the reviews if their children retrieve the information about the suitability of potential physicians. For these reasons, we are confident that our measure of reviews – even if it is available only at the aggregate city level – proxies well for various channels of the usefulness of reviews for reducing the care gap after a physician's retirement.

Simultaneity and omitted variable bias. Perhaps the most pressing endogeneity concern arises if one of the factors driving the creation of reviews also drives why patients find their physicians faster. Formally, an omitted variable bias results if an unobserved variable correlated with the online reviews is the true reason for shorter care-gaps after physicians retire. Online reviews appear to cause an effect that is due to the omitted factor, hence this threat to identification deserves great attention.

Various unobserved factors might plausibly be correlated to online reviews. First, technological progress may drive both the creation of reviews and reduction in the care gap.

For instance, the better availability of physician websites as well as online patient management and scheduling tools might contribute equally to the reduction in time between visits. Second, the attitudes of a city's population might change over time, causing them to pay more attention to health-related issues. For instance, if a city suddenly has a population with higher income, less poverty and higher education, this might equally lead to a reduction in the average care-gap. Third, government policies that aim to shorten the care-gap might have been implemented primarily in treated cities, where people also adopted the review platform. For instance, access restrictions might have been lowered, and more physicians might have set up offices in a city. The new entrants might be more likely to invest in an online reputation than the incumbents. Similarly, insurance-driven policies (e.g. reminding patients about screening appointments), might have primarily been put into effect in the treated cities and not in the control group.

We address this concern in several ways: First, we control for city-level fixed effects. By doing this, only time-varying factors could lead to the concern over an omitted variable bias. Second, we analyze the time between visits by patients of nonretiring physicians. If there was an underlying dynamic that affected both review generation and the time between visits, this would also be observed among patients of nonretiring physicians. We show in a robustness check that online reviews have little effect on the time between visits for patients of nonretiring physicians. Hence, a bias could only emerge if there were omitted time-varying factors that influence the time between visits only for patients of retiring physicians, but not for those of nonretiring physicians (see Tables 3 and F2). Finally, as a robustness check, we also add several control variables to account for unobserved city-specific heterogeneity over time. These controls include the adoption of broadband internet in the cities in our sample, controls regarding the income and poverty level, and the level of educational attainment. To control for changes in the availability of physicians, we also control for the number of physicians in a specialty in the city.

Selection into treatment. The last major potential source of endogeneity is selection into treatment. As we have argued before, patients cannot select into treatment, as the availability of reviews is exogenous to their need to find a new physician. However, the creation and therefore the presence of online reviews in one city is not necessarily random and is potentially correlated with other location-specific unobserved characteristics that cannot be fully characterized with an independent instrument. This leads to the question of why reviews are available in some cities and not in others and whether the effect on the care gap differs between treated and untreated cities.

First, the creation of reviews likely follows the introduction of Yelp. The use of Yelp depends on broadband availability, internet adoption, and smartphone usage. Moreover, reviews could be present in cities where where patients are more likely to change residence. As said above, these and other factors that drive platform adoption are essentially omitted variables here. Thus, a first step into addressing this concern is including broadband availability, income, educational attainment, and the number of physicians in the area as control variables. In the second step we use an IV based on Yelp reviews in other categories (plumbers and hairdressers). This IV addresses the concern that reviews for physicians could be due to unobserved technology adoption or other developments in the physician's market that coincide with reducing the time between visits and improving follow-up rates. Reviews in other categories cannot be driven by these developments, and cannot affect the care-gap.

Admittedly, factors that drive Yelp adoption could be correlated with health consciousness through several channels, such as income or education. Yelp adoption could also correlate with preferences regarding search costs. For example, consumers who highly value information are willing to invest more in search and may adopt technology to reduce search costs more quickly. We note that our DiD strategy addresses the concern about underlying differences, as long as they are stable over time.

However, our approach could be invalidated if these attitudes toward personal health or search changed at different rates in treated and control cities. We partially address this concern by controlling for income and education and in our pre-trend analysis, which suggests the time between visits in both groups followed parallel trends in the first four years of the period observed.

Although it is unlikely that the creation of Yelp reviews is driven by the desire to find physicians faster, it is possible that review platforms are adopted in places where they are more useful than average. One example of such a situation is heterogeneity in patient engagement levels with the review platform. The population in the control group might fail to write reviews, and their engagement levels might be too low to respond to reviews, even if they existed. In such a case, treatment would become ineffective. We addressed this concern by adding county-level controls for education level, income indicators, broadband availability and the number of physicians in the area. Moreover, if the concern cannot be fully dismissed, then two implications are raised. First, this form of selection into treatment suggests that the effects we find are weaker in places that are slower to adopt review platforms, at least until they catch up in adoption. However, we still quantify a relevant Average Treatment Effect on the Treated (ATT). Second, our study nevertheless highlights the value in designing an engaging and potentially comprehensive review platform, and encouraging patients to use it.

Summary. The main concern with the validity of our DiD approach is potential endogeneity from two sources: selection into treatment and omitting important explanatory variables. Selection into treatment implies that our estimation results represent an ATT. Our results would then apply only partially to the cities in the control group (until they also adopt online platforms for reviews). Omitting a relevant variable that is correlated with online reviews could imply a bias. We address these concerns by adding various controls related to broadband availability, income, education, and the number of physicians. Thereby, the effect of reviews declines for patients of nonretiring physicians. We also highlight in the pre-trend analysis that no shifts in underlying trends occurred. Moreover, we apply an IV strategy based on reviews in other Yelp categories to rule out the possibility that the effect is driven by physician-specific factors such as technology adoption. Consequently, because of the city-level fixed effects and our results for nonretiring physicians (see Table 3), we are most concerned about time-varying factors, which do not (or barely) influence the time between visits of patients whose physicians are not retiring.

D Instrumental variable estimation

D.1 Overview and descriptive statistics

In this section we provide the details of our IV estimation. We provide descriptive statistics of our instruments in Table D1. *n_rev_plumbing* is the number of Yelp reviews for plumbers and *n_rev_hair* is the number of Yelp reviews for hairdressers in a city, respectively. *plumb_revpercap* denotes the number of plumber reviews in a city per capita, and *pct_mds_u*45 is the share of physicians which are younger than 45 years in the county of the respective city.

Table D1: Descriptive statistics for the instrumental variables in the "post" period.

	nobs	NAs	Sum	Mean	Minimum	Maximum
n_rev_plumbing	11,827	0	51,697,324	4,371.127	169	44,484
n_rev_hair	11,827	0	107,001,498	9,047.222	679	53,346
plumb_revpercap	11,827	0	84.458	0.007	0.0004	0.075
pct_mds_u45	11,827	0	4,409.385	0.373	0.223	0.557

In subsection D.3, we provide more detailed results regarding the use of the availability of reviews as an instrument. First, in Table D2, we report the complete results (including first stages) of our IV estimation using the IV based on the number of reviews for plumbers. Columns 1-3 show the results for following up with a new physician within 15 months, and columns 4-6 analyze the days until the follow-up visit took place. Columns (1) and (4) depict the results of our main OLS-specification without instrumenting, and using city-level averages. Columns (2) and (5) depict the results of the 2SLS-IV estimation, and columns (3) and (6) show the respective first stages for each IV-Regression. We investigate then whether our approach is sensitive to the specific craft, and replace reviews for plumbers with reviews for hairdressers in Table D3. Furthermore, we normalize the number of reviews per capita, to use review density instead of the raw number as an instrument (Table D4).

In subsection D.4, we report the results of instrumenting the presence of physician reviews with the share of physicians in a city below 45 years in Table D5. We further report the results of using this variable along with the number of reviews for plumbers as an instrument in Table D6.

Lastly, in subsection D.5 we give an overview over all first-stage estimations and how they compare against the raw regression of the treatment variable on the baseline explanatory variables. As reflected in Tables D7 and D8, there is a large improvement in the R^2. This suggests that our instrumental variable is highly relevant.

D.2 Detailed IV specification for plumber reviews

Table D2: IV estimation using reviews for plumbers as instrumental variable.

	Dependent variable:					
	Follow-up (15months)			Time between visits (Days)		
	Base fup	Fup IV	Fup 1st	Base Days	Days IV	Days 1st
	(1)	(2)	(3)	(4)	(5)	(6)
city_u20	0.432*	0.685***	−2.849***	−522.456***	−583.076***	−3.346***
	(0.238)	(0.246)	(0.053)	(167.148)	(169.643)	(0.077)
city_5064	0.566***	0.792***	−3.455***	−769.348***	−818.654***	−3.380***
	(0.189)	(0.196)	(0.041)	(121.108)	(123.379)	(0.055)
city_6574	−0.239	−0.019	−2.129***	−150.199	−215.731**	−1.695***
	(0.156)	(0.165)	(0.034)	(103.726)	(108.340)	(0.047)
city_75u	0.926***	1.040***	−1.710***	−509.400***	−531.586***	−1.999***
	(0.133)	(0.136)	(0.030)	(88.840)	(89.475)	(0.042)
city_male	−0.184**	−0.174**	−1.671***	−54.187	−70.414	−1.277***
	(0.081)	(0.081)	(0.020)	(69.299)	(69.735)	(0.033)
post	−0.043***	−0.060***	0.073***	22.076***	25.739***	0.013***
	(0.009)	(0.010)	(0.002)	(5.576)	(5.844)	(0.003)
did	0.064***			−40.390***		
	(0.016)			(10.452)		
‘did(fit)‘		0.116***			−55.459***	
		(0.020)			(12.685)	
n_rev_plumbing			0.051***			0.059***
			(0.0002)			(0.0004)
Ref Category	20-49	20-49	20-49	20-49	20-49	20-49
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,113	27,113	27,113	13,007	13,007	13,007

NOTES: This table shows the results of an instrumental variable regression using the number of online reviews for plumbers at the city level as an instrument. Columns (1) and (4) depict the results of our main OLS-specification without the instrument, and are included for reference. Columns (2) and (5) depict the results with an instrument, and columns (3) and (6) are the respective first stages for each sample. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

D.3 Reviews in other Yelp categories

Table D3: Instrumental variable regressions: reviews for hairdressers.

	Dependent variable:					
	fup15mo		did	DAYS		did
	Base fup	Fup IV	Fup 1st	Base Days	Days IV	Days 1st
	(1)	(2)	(3)	(4)	(5)	(6)
city_u20	0.432^{*}	0.395	-0.106^{**}	-522.456^{***}	-492.182^{***}	0.049
	(0.238)	(0.242)	(0.042)	(167.148)	(168.187)	(0.057)
city_5064	0.566^{***}	0.533^{***}	-1.670^{***}	-769.348^{***}	-744.724^{***}	-1.271^{***}
	(0.189)	(0.192)	(0.031)	(121.108)	(122.055)	(0.040)
city_6574	-0.239	-0.272^{*}	-1.806^{***}	-150.199	-117.472	-1.614^{***}
	(0.156)	(0.160)	(0.025)	(103.726)	(105.665)	(0.033)
city_75u	0.926^{***}	0.909^{***}	-0.006	-509.400^{***}	-498.321^{***}	0.201^{***}
	(0.133)	(0.135)	(0.023)	(88.840)	(89.103)	(0.030)
city_male	-0.184^{**}	-0.186^{**}	-1.705^{***}	-54.187	-46.084	-1.324^{***}
	(0.081)	(0.081)	(0.015)	(69.299)	(69.479)	(0.023)
post	-0.043^{***}	-0.041^{***}	-0.058^{***}	22.076^{***}	20.246^{***}	-0.085^{***}
	(0.009)	(0.010)	(0.002)	(5.576)	(5.689)	(0.002)
did	0.064^{***}			-40.390^{***}		
	(0.016)			(10.452)		
‘did(fit)‘		0.056^{***}			-32.864^{***}	
		(0.018)			(11.433)	
n_rev_hair			0.044^{***}			0.048^{***}
			(0.0001)			(0.0002)
Ref Category	20-49	20-49	20-49	20-49	20-49	20-49
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,113	27,113	27,113	13,007	13,007	13,007

NOTES: This table shows the results of an IV-regression that instruments for selection into treatment using the number of online reviews for hairdressers. The first three columns show the results for following up within 15 months, and Columns (4) to (6) show the results for inter-visit times. Columns (3) and (6) show the first stage results for the respective samples. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

Table D4: Instrumental variable regressions: reviews for plumbers per capita.

	Dependent variable:					
	fup15mo		did	DAYS		did
	Base fup	Fup IV	Fup 1st	Base Days	Days IV	Days 1st
	(1)	(2)	(3)	(4)	(5)	(6)
city_u20	0.432*	0.395	−2.499***	−522.456***	−597.442***	−1.289***
	(0.238)	(0.249)	(0.059)	(167.148)	(171.749)	(0.096)
city_5064	0.566***	0.533***	−3.339***	−769.348***	−830.338***	−2.273***
	(0.189)	(0.199)	(0.045)	(121.108)	(125.290)	(0.067)
city_6574	−0.239	−0.271	−3.143***	−150.199	−231.260**	−2.704***
	(0.156)	(0.168)	(0.037)	(103.726)	(112.142)	(0.055)
city_75u	0.926***	0.909***	−1.252***	−509.400***	−536.844***	−0.563***
	(0.133)	(0.137)	(0.033)	(88.840)	(90.014)	(0.051)
city_male	−0.184**	−0.186**	−1.193***	−54.187	−74.259	−1.832***
	(0.081)	(0.081)	(0.022)	(69.299)	(70.105)	(0.040)
post	−0.043***	−0.041***	0.123***	22.076***	26.607***	0.073***
	(0.009)	(0.010)	(0.002)	(5.576)	(6.064)	(0.003)
did	0.064***			−40.390***		
	(0.016)			(10.452)		
‘did(fit)‘		0.056**			−59.030***	
		(0.022)			(14.325)	
plumb_revpercap			24.519***			25.509***
			(0.138)			(0.210)
Ref Category	20-49	20-49	20-49	20-49	20-49	20-49
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,113	27,113	27,113	13,007	13,007	13,007

NOTES: This table shows the results of an IV-regression that instruments for selection into treatment using the number of reviews for plumbers per capita. The first three columns show the results for following up within 15 months, and Columns (4) to (6) show the results for inter-visit times. Columns (3) and (6) show the first stage results for the respective samples. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

D.4 Demographic characters of the physicians

Table D5: Instrumental variable regressions: share of physicians below 45 years of age.

	Dependent variable:					
	fup15mo		did	DAYS		did
	Base fup	Fup IV	Fup 1st	Base Days	Days IV	Days 1st
	(1)	(2)	(3)	(4)	(5)	(6)
city_u20	0.432*	2.870***	−4.701***	−522.456***	−1,416.082***	−3.879***
	(0.238)	(0.557)	(0.084)	(167.148)	(340.876)	(0.135)
city_5064	0.566***	2.738***	−4.161***	−769.348***	−1,496.189***	−3.103***
	(0.189)	(0.486)	(0.066)	(121.108)	(270.041)	(0.097)
city_6574	−0.239	1.887***	−3.945***	−150.199	−1,116.227***	−4.038***
	(0.156)	(0.465)	(0.054)	(103.726)	(336.356)	(0.080)
city_75u	0.926***	2.033***	−2.169***	−509.400***	−836.450***	−1.446***
	(0.133)	(0.265)	(0.048)	(88.840)	(140.921)	(0.073)
city_male	−0.184**	−0.091	−0.131***	−54.187	−293.391***	−1.044***
	(0.081)	(0.085)	(0.030)	(69.299)	(105.942)	(0.057)
post	−0.043***	−0.207***	0.294***	22.076***	76.075***	0.218***
	(0.009)	(0.035)	(0.003)	(5.576)	(18.732)	(0.004)
did	0.064***			−40.390***		
	(0.016)			(10.452)		
‘did(fit)‘		0.569***			−262.529***	
		(0.105)			(74.207)	
pct_mds_u45			−1.456***			−1.293***
			(0.056)			(0.078)
Ref Category	20-49	20-49	20-49	20-49	20-49	20-49
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,113	27,113	27,113	13,007	13,007	13,007

Notes: This table shows the results of an IV-regression that instruments for selection into treatment using the share of physicians aged below 45 as instrumental variable. The first three columns show the results for following up within 15 months, and Columns (4) to (6) show the results for inter-visit times. Columns (3) and (6) show the first stage results for the respective samples. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

Table D6: Instrumental variable regressions: % of physicians below 45 & reviews for plumbers.

	Dependent variable:					
	fup15mo		did	DAYS		did
	Base fup	Fup IV	Fup 1st	Base Days	Days IV	Days 1st
	(1)	(2)	(3)	(4)	(5)	(6)
city_u20	0.432*	0.669***	−2.855***	−522.456***	−576.635***	−3.376***
	(0.238)	(0.246)	(0.053)	(167.148)	(169.626)	(0.077)
city_5064	0.566***	0.778***	−3.473***	−769.348***	−813.415***	−3.424***
	(0.189)	(0.196)	(0.041)	(121.108)	(123.364)	(0.056)
city_6574	−0.239	−0.032	−2.160***	−150.199	−208.768*	−1.749***
	(0.156)	(0.165)	(0.034)	(103.726)	(108.312)	(0.048)
city_75u	0.926***	1.033***	−1.710***	−509.400***	−529.229***	−2.011***
	(0.133)	(0.136)	(0.030)	(88.840)	(89.470)	(0.042)
city_male	−0.184**	−0.175**	−1.694***	−54.187	−68.690	−1.287***
	(0.081)	(0.081)	(0.020)	(69.299)	(69.731)	(0.033)
post	−0.043***	−0.059***	0.076***	22.076***	25.350***	0.017***
	(0.009)	(0.010)	(0.002)	(5.576)	(5.842)	(0.003)
did	0.064***			−40.390***		
	(0.016)			(10.452)		
‘did(fit)‘		0.113***			−53.858***	
		(0.020)			(12.673)	
pct_mds_u45			0.268***			0.331***
			(0.036)			(0.046)
n_rev_plumbing			0.051***			0.060***
			(0.0002)			(0.0004)
Ref Category	20-49	20-49	20-49	20-49	20-49	20-49
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,113	27,113	27,113	13,007	13,007	13,007

NOTES: This table shows the results of an IV-regression that instruments for selection into treatment using both the county level share of physicians below 45 and the number of online reviews as instrumental variable. The first three columns show the results for following up within 15 months, and Columns (4) to (6) show the results for inter-visit times. Columns (3) and (6) show the first stage results for the respective samples. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

D.5 First stage results

Table D7: Comparison of first stages in IV-specification: follow-up.

	Dependent variable:					
	did			NA		
	1st wo IV	IV 1st	IV 1st	IV 1st	IV 1st	IV 1st
	(1)	(2)	(3)	(4)	(5)	(6)
city_u20	−4.825***	−2.849***	−0.106**	−2.499***	−4.701***	−2.855***
	(0.085)	(0.053)	(0.042)	(0.059)	(0.084)	(0.053)
city_5064	−4.299***	−3.455***	−1.670***	−3.339***	−4.161***	−3.473***
	(0.066)	(0.041)	(0.031)	(0.045)	(0.066)	(0.041)
city_6574	−4.208***	−2.129***	−1.806***	−3.143***	−3.945***	−2.160***
	(0.053)	(0.034)	(0.025)	(0.037)	(0.054)	(0.034)
city_75u	−2.191***	−1.710***	−0.006	−1.252***	−2.169***	−1.710***
	(0.049)	(0.030)	(0.023)	(0.033)	(0.048)	(0.030)
city_male	−0.185***	−1.671***	−1.705***	−1.193***	−0.131***	−1.694***
	(0.031)	(0.020)	(0.015)	(0.022)	(0.030)	(0.020)
post	0.323***	0.073***	−0.058***	0.123***	0.294***	0.076***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
n_rev_plumbing		0.051***				0.051***
		(0.0002)				(0.0002)
n_rev_hair			0.044***			
			(0.0001)			
plumb_revpercap				24.519***		
				(0.138)		
pct_mds_u45					−1.456***	0.268***
					(0.056)	(0.036)
Ref Category	20-49	20-49	20-49	20-49	20-49	20-49
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,113	27,113	27,113	27,113	27,113	27,113
R^2	0.754	0.909	0.949	0.887	0.760	0.909
Adjusted R^2	0.754	0.909	0.949	0.886	0.760	0.909

NOTES: In this table we compare the first stage results for the IV regressions that instrument for selection into treatment for the "follow-up sample." The first column shows the results of the first stage without any instruments. Columns 2 and 3 use the number of reviews for plumbers and hairdressers, respectively, as instrumental variables. Column 4 uses the number of reviews for plumbers per capita. Column 5 uses the share of physicians younger than 45, and Column 6 uses both the share of physicians younger than 45 along with the number of reviews for plumbers.
Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

Table D8: Comparison of first stages in IV-specification: time between visits.

	Dependent variable: PostxTreat (i.e. did)					
	1st w/o IV	IV 1st	IV 1st	IV 1st	IV 1st	IV 1st
	(1)	(2)	(3)	(4)	(5)	(6)
city_u20	-4.023^{***}	-3.346^{***}	0.049	-1.289^{***}	-3.879^{***}	-3.376^{***}
	(0.136)	(0.077)	(0.057)	(0.096)	(0.135)	(0.077)
city_5064	-3.272^{***}	-3.380^{***}	-1.271^{***}	-2.273^{***}	-3.103^{***}	-3.424^{***}
	(0.098)	(0.055)	(0.040)	(0.067)	(0.097)	(0.056)
city_6574	-4.349^{***}	-1.695^{***}	-1.614^{***}	-2.704^{***}	-4.038^{***}	-1.749^{***}
	(0.078)	(0.047)	(0.033)	(0.055)	(0.080)	(0.048)
city_75u	-1.472^{***}	-1.999^{***}	0.201^{***}	-0.563^{***}	-1.446^{***}	-2.011^{***}
	(0.074)	(0.042)	(0.030)	(0.051)	(0.073)	(0.042)
city_male	-1.077^{***}	-1.277^{***}	-1.324^{***}	-1.832^{***}	-1.044^{***}	-1.287^{***}
	(0.057)	(0.033)	(0.023)	(0.040)	(0.057)	(0.033)
post	0.243^{***}	0.013^{***}	-0.085^{***}	0.073^{***}	0.218^{***}	0.017^{***}
	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)
n_rev_plumbing		0.059^{***}				0.060^{***}
		(0.0004)				(0.0004)
n_rev_hair			0.048^{***}			
			(0.0002)			
plumb_revpercap				25.509^{***}		
				(0.210)		
pct_mds_u45					-1.293^{***}	0.331^{***}
					(0.078)	(0.046)
Ref Category	20-49	20-49	20-49	20-49	20-49	20-49
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,007	13,007	13,007	13,007	13,007	13,007
R^2	0.746	0.918	0.958	0.881	0.751	0.919
Adjusted R^2	0.745	0.918	0.958	0.881	0.750	0.918

NOTES: In this table we compare the first stage results for the IV-regressions that instrument for selection into treatment for the "inter-visit time sample." The first column shows the results of the first stage without any instruments. Columns 2 and 3 use the number of reviews for plumbers and hairdressers, respectively, as instrumental variables. Column 4 uses the number of reviews for plumbers per capita. Column 5 uses the share of physicians younger than 45, and Column 6 uses both the share of physicians younger than 45 along with the number of reviews for plumbers. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

E Controlling for potentially omitted factors

In this section we show that our results are robust by controlling for potentially omitted variables. These additional control variables are related to the internet infrastructure, demographics (income, poverty, education), and the availability of physicians. Regarding the availability of physicians, we have retrieved the number of physicians in each county of the respective cities were patients live.

County level data on income, poverty, education, and physician counts were obtained from the 2019-2020 release of the county level Area Health Resources File (AHRF) of the Health Resources and Services Administration.[15] The AHRF combines data from many sources including the American Community Survey (ACS), American Medical Association (AMA) Physician Masterfile, American Hospital Association Survey data, and a wealth of census data. More specifically, physician counts by age and speciality for the pre- and post-treatment periods were obtained from the 2010 and 2018 entries found in the AHRF, and are originally sourced from the AMA Physician Masterfiles released in March 2012 and July 2020, respectively.

Poverty rates corresponding to the years 2010 and 2018 served as our poverty controls for the pre- and post-treatment period, respectively. This data is originally sourced from the April 2013 and July 2020 releases of the U.S. Census Bureau's Small Area Income and Poverty Estimates.

Per capita personal income data for the years 2010 and 2018 served as pre- and post-treatment income controls. This data was originally sourced from the July 2019 release of the Bureau of Economic Analysis' Local Area Personal Income data.

Lastly, the portion of residents age 25+ with a 4 year college degree or higher from the 2011-2015 and 2014-2018 5-year ACS served as our education controls for the pre- and post-treatment periods, respectively.

The data on internet infrastructure were obtained from Form 477 county data on internet access services made publicly available by the Federal Communications Commission.[16] Values for the pre-treatment period were obtained from the December 31, 2008 release of county level Form 477, whereas the post-treatment period values were obtained from the December 31, 2018 release of county level Form 477.

County level data were mapped to zip codes using a 2018Q4 zip code to county crosswalk file by the U.S. Department of Housing and Urban Development.[17]

The total number of physicians is given by mds_tot, and the share of these which have an age lower than 45 years is given in mds_u45. To control for demographic properties of the respective cities, we have collected the average income per capita ($percap\_inc$), the

[15] See https://data.hrsa.gov/data/download

[16] See https://www.fcc.gov/form-477-county-data-internet-access-services

[17] See https://www.huduser.gov/portal/datasets/usps_crosswalk.html

share of inhabitants in povery (*pct_pov*) to measure the wealthiness of the population. Furthermore, we collected the share of population with a 4 year college degree (*pct_clg*) as a measure for educational attainment. Finally, to control for the availability of broadband internet, we have gathered the share of households in a county with broadband access, according to the Federal Communications Commission (variable *hspd_ratio*). This information was not available for all counties, explaining the loss of observations in the results in Columns (3) and (4) in Table 3.

Table E1: Descriptive statistics for additional controls.

	nobs	NAs	Sum	Mean	Minimum	Maximum
mds_tot	27,113	0	143,182,743	5,280.963	207	36,510
mds_u45	27,113	0	53,930,086	1,989.086	55	12,221
percap_inc	27,113	0	1,243.664	0.046	0.026	0.131
pct_pov	27,113	0	427,030.200	15.750	4.200	31.500
pct_clg	27,113	0	908,810.300	33.519	17.100	57.800
hspd_ratio	27,113	4,075	16,448.750	0.714	0.300	1.090

We report descriptive statistics for these variables in Table E1. We also report a correlation matrix in Table E2. As expected, we find strong positive correlations between the average income in a city and the percentage of residents with a college degree, which are also both negatively correlated with the share of inhabitants in poverty.

Table E2: Correlation matrix for control variables.

	TREAT	pct_clg	percap_inc	pct_pov	mds_tot	mds_u45	hspd_ratio
TREAT	1	0.347	0.207	−0.266	0.598	0.571	0.114
pct_clg	0.347	1	0.711	−0.711	−0.083	−0.066	0.374
percap_inc	0.207	0.711	1	−0.489	0.086	0.110	0.498
pct_pov	−0.266	−0.711	−0.489	1	0.105	0.136	−0.522
mds_tot	0.598	−0.083	0.086	0.105	1	0.979	−0.007
mds_u45	0.571	−0.066	0.110	0.136	0.979	1	−0.035
hspd_ratio	0.114	0.374	0.498	−0.522	−0.007	−0.035	1

Table E3: Regression results when adding control variables: follow-up in 15 months.

	Dependent variable: fup15mo						
	Base	educ	inc	pov	mds	hspd	all
pct_clg		0.002					0.001
		(0.001)					(0.002)
percap_inc			-0.002^{**}				-0.002^{**}
			(0.001)				(0.001)
pct_pov				-0.010^{***}			-0.011^{***}
				(0.002)			(0.003)
mds_tot					-0.00000		0.00001^{*}
					(0.00000)		(0.00000)
hspd_ratio						0.133^{**}	0.040
						(0.057)	(0.062)
age_u20	0.002	0.002	0.00003	0.002	0.002	-0.005	-0.008
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
age_5064	0.089^{***}	0.089^{***}	0.089^{***}	0.089^{***}	0.089^{***}	0.084^{***}	0.085^{***}
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
age_6574	0.182^{***}	0.182^{***}	0.183^{***}	0.183^{***}	0.182^{***}	0.174^{***}	0.176^{***}
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
age_75u	0.204^{***}	0.204^{***}	0.205^{***}	0.206^{***}	0.204^{***}	0.204^{***}	0.206^{***}
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
male	0.019^{***}	0.019^{***}	0.019^{***}	0.019^{***}	0.019^{***}	0.018^{***}	0.018^{***}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
post	-0.057^{***}	-0.060^{***}	-0.039^{***}	-0.079^{***}	-0.056^{***}	-0.076^{***}	-0.056^{**}
	(0.009)	(0.009)	(0.012)	(0.010)	(0.009)	(0.019)	(0.023)
did	0.070^{***}	0.068^{***}	0.083^{***}	0.055^{***}	0.073^{***}	0.053^{***}	0.047^{**}
	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.016)	(0.019)
Ref Category	20-49	20-49	20-49	20-49	20-49	20-49	20-49
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,113	27,113	27,113	27,113	27,113	23,038	23,038
Note:							$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table E4: Regression results when adding control variables: time between visits in days

	Dependent variable: DAYS						
	Base	educ	inc	pov	mds	hspd	all
pct_clg		0.249					2.079
		(0.784)					(1.490)
percap_inc			458.269				815.136
			(504.655)				(863.583)
pct_pov				3.521^{***}			6.393^{***}
				(1.342)			(2.276)
mds_tot					0.001		-0.003
					(0.002)		(0.002)
hspd_ratio						-62.264	-21.544
						(41.669)	(47.995)
age_u20	-24.750	-24.751	-24.704	-24.708	-24.771	-19.209	-18.640
	(15.522)	(15.522)	(15.522)	(15.518)	(15.522)	(16.141)	(16.137)
age_5064	-2.097	-2.146	-2.438	-2.382	-2.119	-1.805	-3.180
	(7.989)	(7.990)	(7.997)	(7.987)	(7.989)	(8.762)	(8.776)
age_6574	-8.664	-8.714	-9.071	-9.150	-8.683	-12.213	-14.242
	(7.843)	(7.845)	(7.856)	(7.843)	(7.843)	(8.648)	(8.677)
age_75u	-9.931	-9.982	-10.322	-10.512	-9.962	-14.271^{*}	-16.392^{*}
	(7.751)	(7.753)	(7.763)	(7.752)	(7.752)	(8.529)	(8.559)
male	-10.349^{***}	-10.356^{***}	-10.340^{***}	-10.224^{***}	-10.343^{***}	-9.879^{***}	-9.725^{**}
	(3.505)	(3.505)	(3.505)	(3.504)	(3.505)	(3.829)	(3.827)
post	24.943^{***}	24.579^{***}	20.146^{***}	33.253^{***}	24.724^{***}	39.114^{***}	32.672^{**}
	(5.376)	(5.498)	(7.537)	(6.239)	(5.421)	(12.047)	(16.346)
did	-30.685^{***}	-30.864^{***}	-33.685^{***}	-26.531^{***}	-31.441^{***}	-32.919^{***}	-28.889^{**}
	(9.131)	(9.149)	(9.710)	(9.265)	(9.439)	(10.340)	(13.039)
Ref Category	20-49	20-49	20-49	20-49	20-49	20-49	20-49
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,007	13,007	13,007	13,007	13,007	10,872	10,872

Note: *p<0.1; **p<0.05; ***p<0.01

F Placebo test for patients of nonretiring physicians

In this appendix we describe in more detail the construction of our placebo test for nonretiring physicians.

For the box plots (Figure **??**) of time between visits, we have constructed the following measures:

- Non_ret: The mean time between visits (in days) for patients of a nonretiring physician across all visits within a given speciality leading up to a placebo retirement date. The placebo retirement date is assigned according to a scaled uniform random variable spanning the range of possible retirement dates in the retiring sample.
- Before_ret: The mean time between visits (in days) for patients of a retiring physician across all visits in a given speciality leading up to their physician's retirement.
- After_ret: The time (in days) between visits surrounding the physician's retirement, i.e. the number of days between the last visit before retirement, and the first visit to a new specialist.

We constructed the nonretiring sample in a manner nearly identical to that used to construct the retiring sample. Two key differences distinguish the nonretiring sample from our main sample of retiring physicians. First, In the nonretiring sample, physicians were labelled as nonretiring if they were active for *every* month of our observation period. Second, a placebo retirement date was assigned by sampling from a scaled discrete uniform random variable with a range matching that of observed retirement dates from the retiring sample.

We verify the consistency and robustness of our placebo test for nonretiring physicians in three main ways. First, we confirm that the patterns for the probability of a follow-up visit within 15 months emerge consistently for all specifications. This analysis, which is shown in Table F1, indicates the follow-up probability is actually estimated to *decrease* by 0.8 percentage points in treated cities.

Second, we ensure that the placebo results are not driven by how we impose the placebo retirement dates. Therefore, we use a patient's average inter-visit time over the whole period of observation as a dependent variable, without using a placebo retirement date. The results in Table F3 suggest that the average time between visits to nonretiring physicians are not significantly different in treated and untreated cities. The effect of online reviews translates to .87 fewer days in treated cities relative to untreated cities, but is not significant.

Finally, in Table F2 we provide the analogous analysis for the number of days until a patient's next visit to any physician within the same speciality. We observe that in comparison to the findings in Table B6, the effect of reviews on the time between visits for patients of nonretiring physicians becomes negligible. To be precise, the coefficient is around 3.6 days (a decrease of 88%), and it is no longer statistically significant. This is despite the drastic increase in statistical power that results from the much larger sample size. These results lead us to conclude that there could be a background tendency of seeing physicians more frequently in treated cities, but this tendency is very small and explains only 12% of the effect we find.

Table F1: Patients of nonretiring physicians: Follow-up within 15 months.

	Dependent variable: Follow up within 15 months			
	Base	Speciality	Patient	City Growth
	(1)	(2)	(3)	(4)
age_u20	0.015***	0.015***	0.013***	0.015***
	(0.004)	(0.004)	(0.004)	(0.004)
age_5064	0.087***	0.087***	0.088***	0.087***
	(0.002)	(0.002)	(0.003)	(0.002)
age_6574	0.172***	0.172***	0.174***	0.172***
	(0.003)	(0.003)	(0.003)	(0.003)
age_75u	0.223***	0.223***	0.219***	0.223***
	(0.003)	(0.003)	(0.004)	(0.003)
male	0.016***	0.016***	0.020***	0.016***
	(0.002)	(0.002)	(0.002)	(0.002)
post	0.029***	0.028***	0.029***	0.028***
	(0.003)	(0.003)	(0.003)	(0.003)
did	−0.008**	−0.024***	0.00001	−0.008**
	(0.004)	(0.005)	(0.005)	(0.004)
did_derm		0.030***		
		(0.005)		
did_infc_gast		−0.005		
		(0.007)		
did_psych		0.018*		
		(0.011)		
did_male			−0.016***	
			(0.004)	
did_u20			0.009	
			(0.008)	
did_5064			−0.008	
			(0.005)	
did_6574			−0.013*	
			(0.008)	
did_75u			0.046***	
			(0.009)	
did_lowgrwth				0.068***
				(0.026)
did_medgrwth				−0.001
				(0.007)
Ref Category	20-49	DiD×Card	DiD× Fem ×20-49	DiD ×HiGrowth
Patient Char.	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	288,436	288,436	288,436	288,436

NOTES: This table analyzes the probability of following up for patients in stable relationships with nonretiring physicians. Follow up within 15 months was evaluated based on a randomly imposed placebo retirement date. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

Table F2: Time between visits immediately before and after a placebo retirement for patients of nonretiring physicians.

	Dependent variable: Number of days until the next visit following a placebo retirement			
	Base (1)	Speciality (2)	Patient (3)	City Growth (4)
age_u20	−41.890***	−41.870***	−43.442***	−41.909***
	(2.421)	(2.421)	(2.856)	(2.421)
age_5064	7.641***	7.535***	5.808***	7.674***
	(1.399)	(1.400)	(1.626)	(1.399)
age_6574	−7.552***	−7.576***	−8.827***	−7.566***
	(1.800)	(1.800)	(2.008)	(1.800)
age_75u	−18.622***	−18.556***	−16.928***	−18.587***
	(1.914)	(1.915)	(2.078)	(1.915)
male	−11.514***	−11.537***	−11.194***	−11.509***
	(1.051)	(1.051)	(1.187)	(1.051)
post	2.722*	2.478	2.387	2.743*
	(1.637)	(1.645)	(1.640)	(1.637)
did	−3.574	0.345	−4.728	−2.791
	(2.244)	(3.057)	(2.980)	(2.339)
did_derm		−5.529*		
		(3.060)		
did_infc_gast		1.031		
		(4.446)		
did_psych		−15.930***		
		(5.843)		
did_male			−1.540	
			(2.530)	
did_u20			5.550	
			(5.288)	
did_5064			7.060**	
			(3.072)	
did_6574			6.440	
			(4.201)	
did_75u			−20.245***	
			(4.881)	
did_lowgrwth				−45.324***
				(14.344)
did_medgrwth				−1.875
				(4.364)
Ref Category	20-49	DiD×Card	DiD× Fem ×20-49	DiD ×HiGrowth
Patient Char.	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	160,935	160,935	160,935	160,935

NOTES: This table shows the analysis for patients in stable relationships with nonretiring physicians. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

Table F3: Average time between visits for patients of nonretiring physicians across all visits leading up to the placebo retirement date.

	Dependent variable: average number of days between two visits, by speciality			
	Base	Speciality	Patient	City Growth
	(1)	(2)	(3)	(4)
age_u20	-31.580^{***}	-31.568^{***}	-33.154^{***}	-31.564^{***}
	(1.354)	(1.354)	(1.584)	(1.354)
age_5064	23.511^{***}	23.476^{***}	22.457^{***}	23.504^{***}
	(0.805)	(0.805)	(0.926)	(0.805)
age_6574	20.047^{***}	20.053^{***}	19.162^{***}	20.065^{***}
	(1.047)	(1.047)	(1.164)	(1.047)
age_75u	17.328^{***}	17.370^{***}	17.920^{***}	17.390^{***}
	(1.116)	(1.117)	(1.206)	(1.116)
male	0.664	0.689	1.108	0.669
	(0.611)	(0.611)	(0.690)	(0.611)
post	11.509^{***}	11.397^{***}	11.368^{***}	11.502^{***}
	(0.959)	(0.964)	(0.961)	(0.959)
did	-0.877	-0.361	-1.557	-1.463
	(1.305)	(1.754)	(1.725)	(1.360)
did_derm		0.736		
		(1.786)		
did_infc_gast		-4.058^{*}		
		(2.466)		
did_psych		-3.698		
		(3.280)		
did_male			-2.011	
			(1.477)	
did_u20			5.794^{*}	
			(2.983)	
did_5064			4.139^{**}	
			(1.794)	
did_6574			4.260^{*}	
			(2.469)	
did_75u			-8.617^{***}	
			(2.880)	
did_lowgrwth				-14.034^{*}
				(8.153)
did_medgrwth				5.125^{**}
				(2.507)
Ref Category	20-49	DiD×Card	DiD× Fem ×20-49	DiD ×HiGrowth
Patient Char.	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	173,216	173,216	173,216	173,216

NOTES: This table shows the analysis for patients in stable relationships with nonretiring physicians, and uses patient's average inter-visit time over all visits prior to the placebo retirement date. Standard errors in parenthesis: *p<0.1, **p<0.05, ***p<0.01.

Download ZEW Discussion Papers from our ftp server:

http://ftp.zew.de/pub/zew-docs/dp/

or see:

https://www.ssrn.com/link/ZEW-Ctr-Euro-Econ-Research.html
https://ideas.repec.org/s/zbw/zewdip.html

//
IMPRINT

ZEW – Leibniz-Zentrum für Europäische Wirtschaftsforschung GmbH Mannheim

ZEW – Leibniz Centre for European Economic Research

L 7,1 · 68161 Mannheim · Germany
Phone +49 621 1235-01
info@zew.de · zew.de