Digitizing Doctor Demand: The Impact of Online Reviews on Doctor Choice

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Abstract

We present empirical evidence for the impact of patient reviews on consumers' physician choices. Our study is based on ZocDoc.com—a unique website that integrates patient reviews, and appointment scheduling for physicians on one platform. Using ZocDoc we construct a novel data set consisting of all reviews written for primary care physicians in Manhattan, New York. We then pair these reviews with data on appointments that are booked through ZocDoc, during February-May, 2013. Our data suggest that patient reviews are becoming an important source of reputation for physicians. About 25% of New York primary care physicians are now listed on ZocDoc, and 84% of them have at least 5 reviews. Because ZocDoc displays each physician's rounded average rating to patients, we can use regression discontinuity to identify the causal impact of patient ratings on patient demand. We find that half a star improvement in ratings, on a scale of 1 to 5 stars, leads to a 10% increase in the likelihood, at the mean, that a doctor will fill an appointment.

JEL: D8, I11, L15, L86

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1. Introduction

Credence goods are products, with uncertain properties, whose quality cannot be fully judged by the consumer even after purchase and consumption (Darby and Karni, 1973). This is especially true in the market for physicians where consumers face uncertainty regarding the quality of the treatment received and may rely on imperfect signals to infer quality. Traditionally, consumers have relied on social learning to resolve some of these information asymmetries. For example, consumers may ask their peers to recommend a physician. Even the National Institute for Aging tells patients to "ask people you trust" for physician recommendations. With the onset of social media revolution, consumers seeking physician recommendation can also learn from consumer review websites such as ZocDoc.com, where patients can share their experiences regarding visits to physicians. By enabling large-scale distribution of information from countless other consumers, these consumer review websites can help resolve information asymmetries among a much broader peer group than has been traditionally possible. This paper provides empirical evidence on the impact of patient-created reviews in the market for primary care physicians.

It is not clear whether consumer review websites should significantly affect markets for credence goods. On the one hand, consumer review websites help fill the void left by the absence of any government or nonprofit agency assuming the role of information provider on primary care physician quality. Consumer reviews can also complement or substitute for existing information—education, board certification, and malpractice claims—on physicians, some of which may not be easily available or understood by a lay person. On the other hand, a consumer writing a review cannot fully evaluate the treatment or service received, since he or she is unfamiliar with the intricacies of the medical knowledge possessed by the primary care physician. Further, patient-created reviews can be difficult to interpret—they reflect the views of a non-representative sample of patients, and are subjective. Consumers must also actively look for consumer reviews, in contrast to mandatory disclosure, such as in the case of calorie posting in chain restaurants[1], and electronic commerce settings, for example eBay.[2]

[1] See Bollinger et al. (2010)

[2] See Cabral and Hortaçsu (2010).

Do online consumer reviews affect markets for credence good? Using a novel data set consisting of all reviews for physicians from ZocDoc.com, and data on appointments that are booked through ZocDoc, we present following key findings: (1) a half-star increase in ZocDoc rating leads to a 10% increase in the likelihood, at the mean, that a physician will fill an appointment, (2) physicians with higher number of reviews also have a higher likelihood of filling an appointment, (3) when compared to males, female physicians have a higher likelihood of filling an appointment, (4) on the supply side, physicians update the quantity of appointments supplied on ZocDoc in response to an increase in the likelihood of filling an appointment, and (5) patient ratings capture patient's visit experience, and educational differences of physicians.

To construct the data set for this analysis, we gather all patient reviews written for primary care physicians in Manhattan, New York city, on the popular doctor reservation platform ZocDoc.com. We then pair these reviews with data on appointments that are booked through ZocDoc, during February-May, 2013. We focus on ZocDoc.com because it is a unique website that integrates patient reviews, and appointment scheduling for physicians on one platform. It is also the dominant player in online appointment scheduling, the appointment schedules of multiple physicians are made available on one single platform, making it convenient for consumers to compare physician rating, background information, appointment slots, and book appointment slots. For Manhattan, the website had over 600 physician information, covering about 25% of all actively practicing licensed primary care physicians as of May, 2013. ZocDoc is also one of the fastest growing website, to *find doctors*, in terms of the number of monthly unique visitors.

To investigate the impact of ZocDoc, we first show that changes in a physician's rating are correlated with change in the likelihood of filling an appointment, controlling for physician characteristics, appointment characteristics, and zip level demographic information. However, if changes in a physician's rating are correlated with other changes in a physician's reputation that would have occurred even in the absence of ZocDoc then this relation cannot be satisfactorily interpreted as causal relationship.[3]

[3] See Eliashberg and Shugan (1997) for a detailed description of this problem.

To support the claim that ZocDoc has a *causal* impact on appointment filling likelihood, we exploit the institutional features of ZocDoc to isolate variation in a physician's rating that is exogenous with respect to unobserved determinants of appointment filling likelihood. In addition to individual reviews, ZocDoc presents the average rating for each physician, *rounded to the nearest half-star*. We implement a regression discontinuity (RD) design around the rounding thresholds, taking advantage of this feature. Essentially, we look for discontinuous jumps in appointment filling likelihood that follow discontinuous changes in rating. One common challenge to the RD methodology is gaming: in this setting, physicians may encourage their favored patients to submit positive reviews.[4] We then implement the McCrary (2008) density test to rule out the possibility that gaming is biasing the results. If gaming were driving the result, then one would expect ratings to be clustered just above the discontinuities. However, this is not the case.

Using the RD framework, we find that a physician's average rating has a large impact on appointment filling likelihood—a half star increase leads to a 10% increase in the likelihood of filling an appointment. The identification strategy used in this paper shows that ZocDoc affects demand, but is also informative about the way that consumers use information. If information is costless to use, then consumers should not respond to rounding, since they also see the underlying reviews. However, a growing literature has shown that consumers do not use all available information (Dellavigna and Pollet 2007; 2010). Further, responsiveness to information can depend not only on the informational content, but also on the simplicity of calculating the information of interest (Chetty et al. 2009, Finkelstein 2009).

Next, we examine the impact of ZocDoc on how soon an appointment gets filled. This will inform us on the way ZocDoc is used by consumers. ZocDoc claims that most of the appointments get booked within a 24-72 hour window. If cancelling an appointment is costless, consumers may want to lock-in a convenient appointment slot with their favorite physician early on. However, if cancellations are costly consumers may be discouraged to book appointments early on and look for last minute appointments. We find that out of the appointments that are filled almost 45% get filled in the last 24 hours. Though we find that ratings are positively

[4] ZocDoc makes is difficult for physicians to submit fake reviews. Only patients who have been verified to have visited the physician after booking an appointment through ZocDoc are encouraged to leave feedback.

correlated with when an appointment gets filled, we do not find satisfactory evidence that ratings have a causal impact on when an appointment gets filled. The RD estimates are not statistically significant for some of our specifications.

We then investigate how physicians respond to the consumer demand on ZocDoc. ZocDoc charges a monthly subscription of $250 from each physician. If ZocDoc is profitable to the physician, as it claims, we should see physicians' making more of their appointments available through ZocDoc over time. Physicians do not post all of their appointments on ZocDoc—on average each physician lists 7 appointments, of 30 minute or less, on any given day. There is a large scope for physicians to make more of their appointment slots available through ZocDoc. We ask whether physicians who see their appointments getting filled, offer more appointments in future. We compare the number of appointments offered on a given date with the average number of appointments for last seven days. We include as an independent variable the probability of filling an appointment in the last seven days. We find that the number of slots posted by a physician is positively correlated with the likelihood of the appointments getting filled.

Overall, this paper presents evidence that consumers use ZocDoc to learn more about physicians. In health care markets, there is strong evidence that public disclosure of health care quality report cards, based on outcome measures, has been effective in better matching patients with products and providers.[5] However, reporting of outcome measures may soon be eclipsed as an information source by consumer review websites such as ZocDoc.com, which are now leveraging social media to disseminate patient-created reviews of physicians. With the crowd-sourcing of opinions enabled by consumer review websites, we can have access to a large amount of information. Consumer review websites may shine the most in the case of individual providers, such as primary care physicians, where effective quality reporting has been more elusive.

[5] For an example of impact of report cards in insurance plan market see Dafny and Dranove (2008) and Jin and Sorensen (2006). and Bundorf et al. (2009). For an example of the impact of report cards on fertility clinics and hospitals see Bundorf et al. (2009), and Cutler et al. (2004) respectively. For an example of report cards on the demand of individual physicians see Wang et al. (2011). However, there is a serious downside risk of selection by providers, due to these report cards, Cardiac surgery report cards in New York and Pennsylvania led to selection by providers (Dranove et al., 2003). Werner et al. (2009) and Lu (2012) find similar evidence with the Nursing Home Quality Initiative.

This paper shows that consumer reviews can be used to solve the information asymmetry in credence goods markets. The paper contributes to the empirical literature on product quality, consumer reviews, and consumer choice in the crucial area of health care markets.

The outline of the paper is as follows: section 2 provides a description of ZocDoccom, section 3 details the data construction process used for the paper, section 4 summarizes the data, section 5 provides an outline of the empirical strategy, section 6 documents the regression results, finally section 7 concludes.

2. Background on ZocDoc.com

ZocDoc, launched in 2007, is an online medical care search, and scheduling service available to patients free-of-charge. The website enables patients to search for physicians by insurance, location, specialty, procedure, hospital affiliation, gender, and languages spoken. Based on the selection criteria ZocDoc provides patients with a list of physicians, patients can view open slots in physicians' schedules and make an appointment online, without ever having to pick up the phone. About 40 percent of these appointments take place within 24 hours[7], much faster than the average appointment wait time of 21 days.[8] According to ZocDoc,[9] most of the appointments happen in 24-72 hour window. ZocDoc appointment service was initially limited to dentists in Manhattan, now ZocDoc claims to serves 40 percent of the U.S. population across more than 1,800 cities. More than 2.5 million patients use ZocDoc to find doctors every month.

On October 18, 2013 we searched for the term *Find Doctors* using Google, Bing, and Yahoo. We picked up all the website names that came up on the first page after the search, that allow users to search for physicians. This exercise gave us 12 websites excluding Yelp.com, AngiesList.com and Kudzu.com. We include these three websites following Kadry et al. (2011). Using Compete.com, a website traffic analysis service, we compare the number of unique

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[7] Kaiser Health News, "More Patients Making Appointments Online As Doctors Embrace Web" http://www.kaiserhealthnews.org/stories/2011/january/03/zocdoc.aspx (Accessed Nov. 19, 2012)

[8] Merritt Hawkins & Associates in a 2009 survey of 1,162 medical offices in 5 specialties across 15 metropolitan areas report an average wait period of 21 days.

[9] http://www.zocdoc.com/aboutus

visitors to these websites, beginning September, 2011. Table 1 ranks these websites by the number of unique visitors in the month of September, 2013. ZocDoc.com ranks 8th out of a total of 14 websites. Figure 1 plots the cumulative monthly change in the number of unique visitors to these websites since September, 2011. ZocDoc.com ranks 2nd, after yellow pages (YP.com), in the cumulative growth rate of number of unique visitors to the website. It is important to note that websites such as YP, Yelp, and Angieslist are all-purpose information websites and it was impossible to dissociate the visits related to doctors from visits to these sites for other purposes such as for restaurant, or plumber quality information. Lately, ZocDoc is looking to expand in new markets—Australia, Brazil, Canada, China, France, Germany, India, Italy, Japan, Mexico and United Kingdom.

Figure 2 displays how the ZocDoc website's opening page looks like. It shows how a patient looking for physicians on ZocDoc can use the website's search feature to obtain a list of specialist physicians who accept a particular health plan. For example, Figure 3 shows a snapshot of the list of primary care physicians in New York City with no restriction on the type of insurance they accept. This is the page that opens up after the search command; it displays the physician's photograph, practice address, rounded average rating, main specialty, medical degree, hospital affiliation, and all open slots in his appointment schedule for the current week. Clicking on any physician name takes the patient to the physician's profile page which displays additional information about the physician's education, specialty, languages spoken, types of insurance accepted, and also displays the detailed ratings and text reviews left by any patient. Figure 4 and Figure 5 display an example of physician profile and the individual patient ratings as they appear on ZocDoc's physician profile page.

ZocDoc does not charge anything from the patients, however physicians can choose to subscribe by paying a monthly subscription of $250. For each subscribing physician the website has a profile page with '*verified'* credentials, and most importantly patient–submitted reviews and ratings. Subscribing physicians benefit by attracting new patients, and by filling the last minute cancellations and postponements (10-20 percent of total appointments)[10] by ZocDoc

[10] ZocDoc's co-founder and CEO Cyrus Massoumi, http://blogs.webmd.com/health-reform-101/2012/05/doctors-appointments-just-a-click-away.html.

patients. The automated reservation system cuts back on the time it takes to schedule an appointment, allowing staff to focus on serving the patients present at the practice.

After the appointment ZocDoc emails a thank-you note, encouraging patients to review and rate (from 1-5 stars) their physicians for bedside manner, wait time and overall impression. The patient can then rate the physician they visited and can also enter a text review. ZocDoc also asks permission to use patient's name and appointment date in the review that will be displayed on the physician's webpage (Figure 6). Once a review is written, anyone (with or without an account) can access the website for free and read the review. Patients will come across reviews within the context of the search for a physician. This allows the patients, looking for physicians on ZocDoc, to compare and assess them on common quality characteristics. Since each *verified* patient is encouraged to leave a review, it may not be that patients who have had extreme experiences, and who are proactive, are the only ones to leave reviews. There is an implicit selection bias to websites that depend on the user to actively engage the review site and write a review, sometimes positive ratings are written by physicians themselves (Lagu et al., 2010), and negative ratings are by disgruntled employee, an ex-spouse, or a competitor (Segal, 2009). By bundling review requests with appointments ZocDoc reduces the selection bias that limits the value of physician ratings.

3. Data Construction

Using ZocDoc.com we generated a unique data set containing physician's appointment schedules and professional information. For the purpose of this study we focus on Primary Care Physicians in Manhattan, one of the five boroughs (municipal corporations) in the city of New York. Using ZocDoc's search engine, we first compile a list of Primary Care Physicians in Manhattan that subscribe to ZocDoc's scheduling service.[11] For each physician that belonged to this list we download[12] their appointment schedule—for the next seven days[13]—available at the

[11] We use the programming language Active Perl 1.4 for this step.

[12] The appointment data is downloaded in a text format using the programming language Python 2.7.

[13] We also attempted to download longer time horizon for available appointment data. We downloaded all open appointment date and time slots for the next twenty-eight days for the period between March 28,

ZocDoc website. We also downloaded detailed physician profile as well as each individual rating and text review. This exercise was repeated daily at 6:00am in the morning over approximately a period of three months, from February 24, 2013 to May 11, 2013.[14] Each day we downloaded the following information:

- All open appointment date and time slots for the next seven calendar days.
- Physician's Personal Information
    - Education: Medical School and Residency
    - Hospital Affiliations
    - Languages spoken
    - Board Certifications
    - Awards and Publications
    - Specialties
- Practice address
- Rounded average physician rating as displayed on physicians profile page
- In-network insurance
- ZocDoc Physician Awards:- These awards located on a physician's profile page inform the patients about the physician's strength on ZocDoc helping them to make an informed choice. These physician awards are,
    - Rapid registration:- Provides digital registration forms to be filled online through ZocDoc Check_in.
    - See You Again:- If a large number of ZocDoc patients book repeatedly with a physician.

2013 to April 11, 2013, however we had to abort the longer horizon data collection due to frequent website updates by ZocDoc.

[14] Our data collection ended on May 11, 2013. In the month of May, ZocDoc started making changes to the various HTML elements of the website. These changes typically went online in the middle of the night, which gave us only a few hours to update our code before the scheduled run at 6:00am. We had to abort the data download process after May 11, 2013 due to frequent changes on the website which were creating interruptions in the daily data download process making it difficult to observe the daily changes in the appointment schedule.

    - Speedy Response:- Physicians who confirm their appointments within one business hour even for same day appointments
    - Scheduling Hero:-Physicians who keep their schedule and in-network insurances up-to-date
- Individual patient rating and review information for each physician
    - Patient name if disclosed by patient
    - Date when the rating was given
    - Number of star ratings under the following categories
        - Overall
        - Bedside manner
        - Wait Time
    - Text Reviews

We further augment the ZocDoc data by physician practice zip code level demographic information from the American Community Survey (ACS) available from US Census Bureau website. We download information on age, sex, race, family, household income, education, where you work and how you get there, and where you live for each zip code in our data set. We specifically use zip code level age and racial distribution, household income, percentage of population working from home, average family size, percentage of households as married-couple families, educational attainment of the population, and percentage of population in the same house as a year ago in our analysis.

4. Data Description

We began with a list of 697 physicians but after merging the physician profile data with the daily appointment data we are left with a subset of 411 physicians. This is because over the period of downloading the data set many physicians had no appointments available for our download window of 77 days. Finally out of 411 physicians 14 physicians do not authorize ZocDoc to reveal their rating data for the entire period of our download window, therefore we are left we a sample of 397 physicians for our analysis.[15] According to the data on all actively

[15] The theory on quality data disclosure (Grossman, 1981; Board, 2009; Jin, 2005) suggests that providers who have not been competing on quality may be reluctant to call attention to their quality differences.

practicing primary care physician in New York maintained by School of Public Health, University at Albany there were 2,599 actively practicing primary care physicians (General Practice, and Internal Medicine) in New York, in 2010.[16] This means that 18 percent of the primary care physician population in new York is on ZocDoc.

4.1. Physician Profile Data

Out of a total of 397 physicians around 59 percent physicians state their primary specialty as internal medicine, while 27 percent of physicians state either primary care, or family medicine. As reported in table 2, close to 40 percent of the physicians are female, while around 45 percent of the physicians have a non-US medical degree. Most physicians have a board certification, close to 70 percent are affiliated to a hospital while 48 percent are affiliated to a teaching hospital. Around 28 percent of physicians list at least one award or publication. Spanish is the second language most often spoken by the physicians, around 45 percent of the physicians speak Spanish. Among the variety of languages spoken by the physicians—we have more than 15 language groups—Russian and related languages, French, and Chinese are the other notable ones.

In our sample 3 physicians accept no insurance, i.e., they accept only private payment. Of the remaining physicians all accept Preferred Provider Organization plans (PPO), while more than 95 percent accept each of the following: Health Maintenance Organization (HMO), Point-of-Service (POS), Exclusive Provider Organization (EPO), and Open Access plans. Out of the physicians who accept insurance, on average a physician accepts 72 different insurance providers, i.e., on average 72 different insurance providers are in a physician's network. Out of all physicians who accept insurance plans more than 80 percent accept Medicaid, and about 96 percent accept Medicare and all accept private insurance plans.

Majority of physicians (around 63 percent) are running their own single physician practices. More than 52 percent of physicians provide digital registration forms to be filled

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[16] http://chws.albany.edu/archive/uploads/2013/09/nys_health_workforce_planning_data_guide_2013.pdf. Accessed October 10, 2013.

online through ZocDoc Check_In and around 72 percent of physicians confirm their appointments within one business hour even for same day appointments.

4.2. Physician Rating Data

ZocDoc displays the physician's rating at two different levels—the physician's rounded average rating for overall impression, and the individual patient ratings for each quality indicator, i.e., bedside manner, wait time and overall impression. The physician's rounded average rating for overall impression, which we download for our analysis, is what is displayed next to the physician's name and photograph (Figure 3 and Figure 4). These prominently displayed ratings are average rating for overall impression that are rounded to the nearest half star. For example, a physician with an average rating of 4.74 on overall impression will be rounded down to 4.5 stars, while a physician with average rating of 4.75 stars will be rounded up to 5 stars, This variation in average rating that is displayed to the patients is exogenous to physician quality and can be exploited for a regression discontinuity analysis. These two physicians (with average rating of 4.74 and 4.75) have comparable average rating for overall impression but have a half-star gap in what is actually displayed to a patient who is comparing physicians on ZocDoc before booking an appointment.

As stated before, all historical patient rating on each of the three quality indicators and the text review data are also displayed on the profile page of each physician (Figure 5) which we download for our analysis. For the overall impression category we find that most patients give their physicians a favorable rating, minimum average rating is 2.8 (Figure 7)[17]. Around 94 percent of the physicians have an average rating of 4 stars or more, while 18 percent of physicians have a perfect 5 star average rating. On average a physician receives overall impression rating from 68 unique patients. The number of patient reviews ranges between a between 1 and 1164 on May 11, 2013. We find that there is a small positive correlation of 0.2 between number of reviews and ratings. Total number of reviews received by a physician can be

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[17] The figure is based on a distribution of ratings on the last day of our data collection exercise, the average ratings for individual doctors do change over the course of our data collection, as new reviews are available, however the distribution of ratings on different days in our sample are quantitatively similar.

an important signal of a physician's popularity on ZocDoc. While looking at the number of reviews we find that the distribution of reviews by their overall rating bins is still skewed to the right but the skewness is reduced when compared to the distribution of physicians by the same rating bins. More than 74 percent of patients who leave a rating after their appointment give a rating of 4.7 or more, but less than 17 percent give a perfect rating of 5 star.

When we look at other rating categories we find that the distribution of rating on bedside manner mimics the rating distribution for overall impression while the distribution of rating for wait time is quite different from distribution of overall impression and bedside. For wait time rating, close to 25 percent of the physicians are rated between 3 to 3.9 stars while physicians with 5 star rating are only around 5 percent of the sample. This is quite different from the ratings on overall impression and bedside manner. For overall impression only 5 percent of physicians are rated between 3 to 3.9 stars and as noted before 94 percent of the physicians have an average rating of 4 stars or more. When we look at the correlation between different rating categories we find that rating for bedside manner and overall impression are highly correlated (correlation value = 0.83), while the correlation between wait time and overall impression is almost half, at 0.44. Similarly, the correlation between bedside manner and wait time is comparatively quite low at 0.31.

In addition to rating their physicians, patients can leave text reviews describing in detail their visit, the conduct of the physician, the staff, and other practice features that the patient would like to bring attention to. We quantified this text data by identifying positive and negative words that are used in the description. An example of some of the positive words used to describe the visit are: *professional, absolutely recommend, cooperative, down-to-earth.* [18]

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[18] The complete list of positive words are—100% recommend, absolutely recommend, accessable, accommodating, actually recommended, Already recommended, amazing, and recommend, answered, approachable, articulate, attentive, awesome, called (should this be included?), cares, Caring, certainly recommend, clean, comfortable, compassionate, Completely recommend, cooperative, courteous, cozy, def recommend, Definitely recommended, detailed, do recommend, down-to-earth, efficient, encouraging, enjoyable, excellent, explained, Extremely recommended, fantastic, friendly, fully recommend, gentle, genuine, glad, gladly recommend, good, great, happily recommend, happy, have recommended, heartedly recommend, helpful, HIGHLY recommend, Honest, humble, I recommend, I'd recommend, impressed, informative, I've recommended, knowledgeable, listens, nice, patient, personable, pleasant, pleasure, polite, positive, professional, really recommend, relaxing, respectful, satisfied, satisfying, sensitive, sincere, smart, strongly recommend, surely recommend, sweet, sympathetic, thorough, thoroughly, thoughtful, totally recommend, transparent, very apologetic, very friendly, Very kind, very well,

Similarly, some of the negative words used to describe the data are: *cluttered, cold, disrespectful, horrible*.[19]

Comparing rating data across different categories of physicians we find that male physicians have a slightly higher average rating (4.58 stars) for overall impression as compared to that for females (4.52), but this difference is not statistically significant. The physicians with a US medical degree are rated 4.62 for overall impression as compared to 4.48 for physicians trained outside US, and we find this difference to be statistically significant at 1 percent level. Physicians who are board certified have an average rating for overall impression of 4.57 stars compared to 4.51 stars for physicians who are not, though this difference is not statistically significant. Similarly the physicians who are affiliated to a hospital have a higher rating as compared to physicians who are not affiliated to a hospital but again this difference is not statistically significant. Finally, the physicians who have stated receiving any award or publication are rated higher at 4.62 stars for overall impression as compared to physicians who do not list any (4.54). This difference is statistically significant at 10 percent level. Table 3 reports the results of a simple regression of overall rating on bedside manner rating, wait time rating, physician profile variables (gender of doctor, dummy variables for US medical degree, awards and publications, and teaching hospital affiliation), and ZocDoc Physician awards. The regression shows that apart from bedside manner rating and wait time rating, the only other significant variable is US medical Degree. Having US medical degree has a positive and significant impact of average physician rating.

Veryrefreshing, warm, welcoming, well-spoken, wholeheartedly recommend, will recommend, Wonderful, Would recommend, yes recommend.

[19] The complete list of negative words are—abrasive, abrupt, alarmist, aloof, annoyed, annoying, Awful, blunt, brusque, Can't recommend, cannot recommend, cluttered, cold, condescending, couldn't recommend, Didn't apologize, dingy, disappointed, disappointing, disgruntled, dismissive, disorganized, disrespectful, don't recommend, embarrassing, go somewhere else, HORRIBLE, indifferent, intimidating, irritated, never recommend, NEVER recommend, never returning, non Clean, not recommend, not recommend, not returning, not very welcoming, not worth, quick, Rude, rushed, scared, shabby, shocked, Strange, Terrible, unapologetic, uncomfortable, unhelpful, unnecessary tests, unorganized, unpolite, unprofessional, unskillful, vague, weirdo, wouldn't recommend.

4.3. Appointment Data

As explained before every day we are downloading all available open slots in a physician's appointment schedule for the next seven days. On a given day (*t*) we observe the appointment slots that are still open for that day, these slots are labeled as "not filled." We also observe the slots that are available for the next six days, *t+1* to *t+6*. The data on available slots for next six days, can be compared with the data that will be downloaded on those days.

For example, on day (*t*) we observe the appointment slots that are open for day *t+1*, some of these slots would still be open when we download data next day, and some will no longer be available. The slots that are no longer available are labeled as "filled," further we know that these slots were filled in last 24 hours.

$$\begin{array}{llllllllll} Download\ Day\ t: & \{day & t & t+1 & t+2 & t+3 & t+4 & t+5 & t+6\} & \\ Download\ Day\ t+1: & \{day & & t+1 & t+2 & t+3 & t+4 & t+5 & t+6 & t+7\} \end{array}$$

Using the appointment data we construct the following variables

- Appointment Filled:

  $$\left\{\begin{array}{l} 1: if\ the\ slot\ is\ not\ open\ on\ the\ \ morning\ of\ appointment\ date \\ 0: if\ the\ slot\ is\ open\ on\ the\ morning\ of\ appointment\ date \end{array}\right\}$$

- Appointment Time: Time of the day corresponding to the appointment slot
- Appointment Date and Day of the week
- Appointment Filled Day

$$\left\{\begin{array}{l} 1: if\ the\ slot\ was\ filled\ 1\ day\ before\ the\ appointment\ date \\ 2: if\ the\ slot\ was\ filled\ 2\ days\ before\ the\ appointment\ date \\ 3: if\ the\ slot\ was\ filled\ 3\ days\ before\ the\ appointment\ date \\ 4: if\ the\ slot\ was\ filled\ 4\ days\ before\ the\ appointment\ date \\ 5: if\ the\ slot\ was\ filled\ 5\ days\ before\ the\ appointment\ date \\ 6: if\ the\ slot\ was\ filled\ 6\ days\ before\ the\ appointment\ date \end{array}\right\}$$

There are 200,383 number of appointments made available by the physicians through ZocDoc for the period of our observation of 77 days which means on average each physician lists 7 slots on any given day while the total number of slots listed on any given day by all physicians is around 2600. We find that the appointment slots are uniformly distributed among the week days, there are appointment slots available for weekends but they add up to less than 10 percent of the total number of appointment slots.

The appointment slots are uniformly distributed during the day with a drop in the number of slots after 4 pm (Figure 8, panel A). The earliest appointment slot available during the data download period is at 6am and the last appointment slot is available for 9.45pm. Out of 200,383 appointments being made available during the period of our observation we observe 90,539 appointments getting filled, i.e., 45 percent of the appointments posted on ZocDoc are getting filled. While looking at the appointment times we find that the appointments before 10am have the highest probability of getting filled, i.e., 85 percent, it declines to 55 percent for appointments between 10-11am, remains uniformly distributed for later hours and then drops to less than 20 percent for appointments after 6pm (Figure 8, panel B). We find that out of the appointments that get filled, about 45 percent are filled within 24 hours of the posted appointment time (Figure 9).

5. Empirical Strategy

We first establish the relationship between physician's rating for average overall impression and the probability of filling an appointment on ZocDoc. Next using a regression discontinuity approach we test the hypothesis that the ratings have a causal impact on the probability of filling an appointment. We next estimate the impact of rating on the quickness of filling an appointment. Finally, we estimate the nature of physician feedback in terms of supply of new appointments in response to the booking of their appointments.

5.1. Impact of Ratings and Reviews on Appointments

To identify the effect of ratings and reviews on appointments we estimate the following model, where i is a physician, and t is an appointment.

$$p = \Pr(Y_{it} = 1) = F\left(\gamma_1 r_{1it-7} + \gamma_2 r_{2it-7} + x'_{1i}\beta_1 + x'_{2i}\beta_2 + z'_j\beta_3\right) \tag{1}$$

$$Y_{it} = \begin{Bmatrix} 1: if\ the\ slot\ is\ not\ open\ on\ the\ morning\ of\ appointment\ date \\ 0: if\ the\ slot\ is\ open\ on\ the\ morning\ of\ appointment\ date \end{Bmatrix}$$

- $r_{1it\text{-}7}$ is the average rating for overall impression for a physician, lagged by 7 days
- $r_{2it\text{-}7}$ is the lagged number of reviews received by the physician (we normalize the number of reviews by the series standard deviation)
- x_{1i}' are the physician specific variables, like gender, languages spoken, education, etc.
- x_{2i}' are the appointment specific variables, like appointment time of the day and appointment day of the week.
- z'_i are the zip code level variables on racial distribution, age distribution, income, family size, etc.

5.2. Regression Discontinuity Framework

For any given day the average physician rating for overall impression that is displayed to the patients is rounded by ZocDoc to the nearest half star. This introduces an exogenous variation in a physician's rating. For example, a physician with a 3.24 average rating will be rounded to 3 stars, while a physician with 3.25 stars will be rounded to 3.5 stars. To analyze the impact of this exogenous variation we look at observations with similar underlying rating but a difference of half star in their rating that is displayed to the patients. We first restrict our sample to observations with less than 0.1 star distance from the discontinuity or the rounding threshold which in this example is 3.25 star. We define a binary variable T:

$$T_{it} = \begin{cases} 0 \; if \; rating \; falls \; just \; below \; a \; rounding \; threshold \; (so \; is \; rounded \; down) \\ 1 \; if \; rating \; falls \; just \; above \; a \; rounding \; threshold \; (so \; is \; rounded \; up) \end{cases}$$

For example, T=0 if the rating ϵ (3.20, 3.25), since a patient looking to book an appointment would see 3 stars as the average rating. Similarly, T=1 if rating ϵ (3.25, 3.30), since the patient would see 3.5 stars as the average rating.

We will estimate the following model:

$$p = \Pr(Y_{it} = 1) = F\left(\theta T_{it-7} + \beta r_{1it-7} + \gamma r_{2it-7} + x_{1i}'\beta_1 + x_{2i}'\beta_2 + z_j'\beta_3\right) \quad (2)$$

where θ is the coefficient of interest. It tells us the impact of an exogenous change in a physician's rating on revenue, θ tells us the impact of moving from below the discontinuity to above it. The remaining variables are as defined in the previous section. We also estimate this model for bandwidths 0.2, 0.3, and 0.4.

5.3. Speed of Appointment Filled

We next estimate the impact of rating on how many days prior to an appointment date does an appointment finally gets filled. We first estimate the following model without the threshold dummy T_{it} to establish the correlation between the speed of appointment getting filled and the ratings. We then estimate the following model to establish the causality.

$$S_{it} = \alpha + \theta T_{it-7} + \beta r_{1it-7} + \gamma r_{2it-7} + x'_{1i}\beta_1 + x'_{2i}\beta_2 + z'_j\beta_3 + \epsilon_{it} \tag{3}$$

where S_{it} is the number of days prior to an open appointment that appointment finally gets filled.

5.4. Supply of Appointments on ZocDoc

As the physician observes his appointments getting filled he might start offering more slots for a given day on ZocDoc. Since we are downloading our data every day we can observe if there is any change in the total number of appointments that any physician makes available on ZocDoc. Therefore, we estimate the following equation

$$S^*_{i\tau,k} = \alpha + \delta F^*_{i\tau,k} + \beta r_{1i\tau} + \gamma_2 r_{2i\tau} + x'_i\beta_x + z'_j\beta_z + \epsilon_{i\tau} \tag{4}$$

where $S^*_{i\tau,k}$ is the number of appointments offered on date τ as a proportion of average number of appointments offered in last k days. $F^*_{i\tau,k}$ the probability of filling the appointment in last k days. We estimate this model for $k=7$ and $k=14$ days.

6. Results

6.1. Impact of Ratings and Reviews on Appointments

Table 4 reports the marginal effects of a simple probit regression, where the dependent variable is equal to 1 if appointment is filled and is equal to 0 if the appointment is open. The regression in column (1) includes average rating for overall impression as the only explanatory variables. The results suggests that ratings have a significant impact on the probability of getting an appointment filled. A one point increase in average rating for overall impression on a five point scale leads to 9 percent increase in the probability of filling an appointment. Regression in column (2) includes the standardized number of patient reviews along with average overall ratings, both variables have significant and positive impact on the probability of filling an appointment. In Column (3) we introduce two variables that describe the content of the text reviews. These are the percentage of negative and positive key words in each doctor's text reviews out of the total word count of the reviews. As one would expect the negative key words words have a negative impact on the physician's probability of getting an appointment filled while the positive key words positively affect the physician's probability of getting an appointment filled. The results of the regression presented in column (4) control for information on the physician in addition to the rating variables, as well as for the time slot and day of the week for each appointment. Notable findings are that female physicians have a higher probability of getting an appointment filled, and early morning appointment slots are more likely to get filled as compared to the afternoon and evening appointments. Regression in column (5) adds the zip level variables from the ACS. To summarize the results in table 4, one point increase in average rating for overall impression on a five point scale leads to 6 percent to 10 percent increase in the probability of filling an appointment. Higher number of reviews also have a positive impact on future demand and female primary care doctors have a higher chance of filling an appointment. In figure 10 and 11 we plot the residuals from marginal probit regression (5) reported in table 4. Figure 10 plots the residuals averaged within 0.1 rating bins, and Figure 11 does the same for bin size to 0.05. All physicians with at least 5 reviews are included in the regression, 4.25 and 4.75 are the two discontinuity points. We see a sharp jump at 4.25 but not much effect at 4.75.

6.2. Regression Discontinuity Framework: Test of Causality

As previously stated ZocDoc prominently displays a physician's rounded average rating for overall impression; however we observe the exact average rating by aggregating the individual patient ratings that we download with our data. Using the exact average rating we can identify the causal impact of ZocDoc ratings on demand with a regression discontinuity framework that exploits ZocDoc's rounding threshold. Table 5, reports the regression discontinuity results. We find that artificially inflating the rating of a physician increases the probability of filling an appointment. In Table 5, Panel A, we report the results for bandwidth size 0.1, i.e. we focus on 0.05 differences in the average actual rating from the either side of the discontinuity. We further examine bandwidth of size 0.2, 0.3 and 0.4. As further evidence in support of our hypothesis we present the results for bandwidth 0.4 in Panel B of Table 5. The results for alternative bandwidth sizes, including those for 0.2 and 0.3 which are not presented in the paper, are similar. We find that a different bandwidth selection mimics the result from those for bandwidth size 0.1. The regression discontinuity approach provides further support to the hypothesis that higher physician ratings as a measure of the quality have a positive impact on the probability of filling open appointment slots.

6.3. Testing for Potential Manipulation of Ratings: McCrary (2008) Test

A possible bias in regression discontinuity results could arise, if the doctors that benefit from ZocDoc by getting more of their appointments filled are more likely to game the system. We test for the evidence of gaming hypothesis based on a test offered by McCrary (2008). If the doctors were gaming ZocDoc ratings, one would expect to see a disproportionately large number of doctors just above the rounding thresholds. Following Luca (2011) the variable of interest is the average rating after each review. Under the hypothesis of gaming, there should be "too many" observations with ratings just above rounding thresholds. To formally test for this, we count the number of observations for each 0.05 star interval, and compute the probability mass for each interval. We create a binary variable to indicate bins that fall just above a rounding threshold (e.g., 4.25-4.3 stars, 4.75-4.8 stars). The dependent variable is the probability mass, and the independent variable is the indicator for bins that fall just above the discontinuity. Table 6 presents the results of this test. The test does not find any clustering of doctors just above the discontinuity, suggesting that manipulation is not an issue with the regression discontinuity design.

6.4. Speed of Appointment Filled

We next examine the impact of physician ratings on the speed at which the appointments get filled. In other words do the physicians who have higher ratings see their appointments getting filled earlier than the other physicians? If the higher rated doctors get their slots filled faster; a patient looking for a physician has the option of either taking an appointment with a lower rated doctor without wait, or wait some extra time for a doctor with higher rating. We run a simple OLS regression the results of which are presented in Table 7. The dependent variable is distance in days of the appointment filled date from the actual appointment date. We expect a longer wait time for a doctor with higher rating. We run parallel regression to the ones reported in table 4. For all the variable combinations we find that the physicians who have higher ratings see their appointments getting filled much earlier. Again female doctors fill up their appointment quicker. Appointment slots for Monday and earlier part of the week get filled relatively quickly. We also examine this hypothesis in a regression discontinuity setting; table 8 reports the results for bandwidth of 0.1. While we find that rounding up the average physician rating leads to an increase on speed at which the appointments get filled, however the results are not statistically significant.

6.5. Supply of Appointments on ZocDoc

Finally we explore the supply of appointments on ZocDoc. We ask whether physicians who see their appointments getting filled offer more appointments in future. We compare the number of appointments offered on date t with number of appointments 7 days earlier. Our dependent variable is the number of appointments on date t as a proportion of average supply in the last 7 days i.e., in the last $t-1$ to $t-7$ days. We include as an independent variable the probability of filling an appointment in the last 7 days. We find that physicians increase their supply of appointments between 6 to 9 percent when they see a 1 percent increase in the probability of filling their appointments (see Table 9). Similarly, we estimate the model while comparing the appointment offered on date t with those offered in the two weeks prior, i.e., from $t-1$ to $t-14$. We find that the impact on the supply of appointments is between 4 to 6 percent (see Table 10). Clearly physicians are responding to successful use of ZocDoc by offering more appointments on the system.

7. Concluding Remarks

As the reach of internet grows we see more and more industries using World Wide Web for improving their services. Websites like Amazon and eBay have become widely used. It is high time that the health care providers benefit from the potential efficiency of the information revolution. In this regard ZocDoc is the first player who is trying to create an online market for physician services, with an intention of helping consumers to make an informed choice regarding the quality of health care provider. Further ZocDoc gives us a peek into how an online market of physician services can be organized and gives us an opportunity to draw lessons from this experiment.

Using ZocDoc.com this paper analyzes a unique data set containing physician's appointment schedules, professional information, and ratings and reviews of former patients. We find that ratings are positively correlated with changes in physician's ability to get more appointments booked through ZocDoc. To support the claim that ratings can have a causal impact on the appointments getting booked, we use the exogenous variability of physician's rating as a tool allowing us to implement the regression discontinuity feature.

In ongoing work, we are exploring the difference between group practices and single physician practices. Physician in group practices share a brand name, and often follow a common treatment style. Therefore, one might expect ZocDoc to have a larger effect on single physician practice than on group practices. Another issue of concern is physician self-selection on ZocDoc. A reputable physician, who is high-in-demand has little incentive to pay ZocDoc a monthly subscription fee, except to cover the last minute cancelations and postponements.

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Table 1: Top 14 Most Frequently Visited Websites to *Find Doctors*

Websites	No. of Unique Visitors (September, 2013)	Rank
Yelp.com	22,824,891	1
HealthGrades.com	6,108,291	2
AngiesList.com	4,416,791	3
Vitals.com	2,205,868	4
HealthLine.com	1,724,830	5
YP.com	1,478,576	6
UCompareHealthCare.com	1,112,753	7
ZocDoc.com	905,051	8
RateMDs.com	509,255	9
Doctor.WebMD.com	454,274	10
Kudzu	264,977	11
Doctor.com	148,142	12
DoctorDirectory.com	9,397	13
FindaDoc.com	1,195	14

Note: On October 18, 2013 we searched for the term *Find Doctors* using Google, Bing, and Yahoo. We picked up all the website names that came up on the first page after the search, that allow users to search for physicians. This exercise gave us 12 websites excluding Yelp.com, AngiesList.com and Kudzu.com. We include these three websites following Kadry et al. (2011). Using Compete.com, a website traffic analysis service, we compare the number of unique visitors (based on IP addresses) to these websites, beginning September, 2011. Table 1 ranks these websites by the number of unique visitors in the month of September, 2013. ZocDoc.com ranks 8th out of a total of 14 websites. The website YP.com is the yellow pages website.

Table 2: ZocDoc - Physician Profile Information

	Population (%)	Average Overall Rating	t-test for difference in means (p-values)
Gender			
Male	61	4.58	0.17
Female	39	4.52	
Education			
US Medical Degree	55	4.62	0.001
Non-US Medical Degre	45	4.48	
Board Certification			
Certified	80	4.57	0.275
Not Certified	20	4.51	
Hospital Affiliation			
Affiliated	69	4.57	0.518
Not Affiliated	31	4.54	
Publications/Awards			
At Least One	27	4.62	0.09
None	73	4.54	

Note: Table 2 shows the average overall rating and frequency distribution of physicians by gender, education, board certification, hospital affiliation and publications/awards.

Table 3: Determinants of Physician's Overall Rating

Dependent Variable: Physician's Average Overall Rating

	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Bedside Manner Rating	0.914***		0.856***		0.861***	0.869***
	(0.045)		(0.043)		(0.042)	(0.043)
Avg. Wait Time Rating		0.252***	0.123***		0.100***	0.088**
		(0.047)	(0.031)		(0.034)	(0.036)
Physician Profile Variables						
Female					0.008	0.014
					(0.019)	(0.019)
US Medical Degree					0.077***	0.064***
					(0.026)	(0.023)
Any Award or Publication					0.043*	0.045*
					(0.024)	(0.024)
Affiliated to Teaching Hospital					0.013	0.016
					(0.018)	(0.020)
ZocDoc's Physician Awards						
Rapid Registration				0.107**		0.047*
				(0.052)		(0.026)
Scheduling Hero				0.054		0.020
				(0.045)		(0.025)
See You Again				0.031		-0.024
				(0.045)		(0.026)
Speedy Response				0.045		-0.006
				(0.067)		(0.034)
Constant	0.333	3.503***	0.085	4.390***	0.098	0.092
	(0.209)	(0.205)	(0.213)	(0.076)	(0.213)	(0.210)
No. of Physicians	397	397	397	397	397	397
Adj R2	0.644	0.154	0.678	0.0391	0.693	0.700

Note: Standard errors are in parentheses and are clustered for physician IDs. ***, **, * denote significance at 1%, 5%, and 10% level respectively. Ratings are on the scale of 1 to 5.

Table 4: Marginal Effects in a Probit Regression: Impact on the Likelihood of Filling an Appointment

Dependent Variable = 1 (if an appointment is filled); 0 (if an appointment is open)

	(1)	(2)	(3)	(4)	(5)
Avg. Overall Rating (Scale: 1 to 5)	0.094***	0.073***	0.056**	0.104***	0.103***
	(0.026)	(0.028)	(0.028)	(0.028)	(0.028)
No. of Patient Reviews (Standardized~(0,1))		0.039***	0.041***	0.032***	0.025***
		(0.008)	(0.008)	(0.009)	(0.010)
Text Review Variables					
Bad Key Words (%)			-0.032**	-0.002	-0.007
			(0.016)	(0.016)	(0.016)
Good Key Words (%)			0.003	0.003	0.004
			(0.003)	(0.003)	(0.003)
Physician Profile Variables					
Female				0.084***	0.080***
				(0.022)	(0.022)
US Medical Degree				-0.118***	-0.125***
				(0.021)	(0.024)
Affiliated to Teaching Hospital				0.086***	0.114***
				(0.020)	(0.021)
Any Award or Publication				0.037	0.042*
				(0.024)	(0.023)
Speaks Spanish				-0.067***	-0.071***
				(0.021)	(0.021)
Appointment Day of the Week Dummy				x	x
Appointment Time of the Day Dummy				x	x
Zip Level Variables					x
Observations	200,123	200,123	200,123	200,123	200,123
No. of Physicians	397	397	397	397	397
LR chi2(1)	13	42	45	1197	1442
Prob > chi2	0.0	0.0	0.0	0.0	0.0
Pseudo R2	0.003	0.007	0.009	0.107	0.122

Note: Standard errors are in parentheses and are clustered for physician IDs. ***, **, * denote significance at 1%, 5%, and 10% level respectively. The unit of observation is an appointment. Bad (Good) key words are expressed as percentage of total text review word count. Zip level demographic variables are from American Community Survey (2011). The zip level demographic variables included are Hispanic (%), White (%), Asian (%), Age 21-64 (%), Age 65+ (%), Works from Home (%), Median Household Income (Standardized~(0,1)), Married-Couple Families (%), Average Family Size, and Same Residence as 1 year ago (%).

Table 5: Regression Discontinuity Approach: Impact on the Likelihood of Filling an Appointment

Dependent Variable = 1 (if an appointment is filled); 0 (if an appointment is open)

Panel A: Bandwidth = 0.1

	(1)	(2)	(3)	(4)	(5)
Threshold Dummy	0.11***	0.10***	0.09**	0.09***	0.11***
	(0.037)	(0.035)	(0.034)	(0.030)	(0.030)
Avg. Overall Rating	x	x	x	x	x
No. of Patient Reviews (Standardized~(0,1))		x	x	x	x
Text Review Variables			x	x	x
Physician Profile Variables				x	x
Appointment Day of the Week Dummy				x	x
Appointment Time of the Day Dummy				x	x
Zip Level Variables					x
Observations	45,071	45,071	45,071	45,071	45,071
No. of Physicians	127	127	127	127	127
LR chi2(1)	9	25	33	428	492
Prob > chi2	0.0	0.0	0.0	0.0	0.0
Pseudo R2	0.010	0.024	0.029	0.142	0.169

Panel B: Bandwidth = 0.4

	(1)	(2)	(3)	(4)	(5)
Threshold Dummy	0.11***	0.10***	0.10***	0.09***	0.09***
	(0.023)	(0.022)	(0.022)	(0.021)	(0.020)
Average Overall Rating	x	x	x	x	x
No. of Patient Reviews (Standardized~(0,1))		x	x	x	x
Text Review Variables			x	x	x
Physician Profile Variables				x	x
Appointment Day of the Week Dummy				x	x
Appointment Time of the Day Dummy				x	x
Zip Level Variables					x
Observations	155,338	155,338	155,338	155,338	155,338
No. of Physicians	308	308	308	308	308
LR chi2(1)	29	52	67	943	1009
Prob > chi2	0.0	0.0	0.0	0.0	0.0
Pseudo R2	0.010	0.017	0.020	0.117	0.140

Note: Standard errors are in parentheses and are clustered for physician IDs. ***, **, * denote significance at 1%, 5%, and 10% level respectively. All physicians with at least 5 reviews are included in the regression. Threshold dummy takes value 0 if the average rating falls below rounding threshold (so is rebounded down to a star), and value 1 if the average rating falls above rounding threshold (so is rebounded up to a star) The unit of observation is an appointment. Regressions include all observations within 0.1 (Panel A) and 0.4 (Panel B) stars of a discontinuity.

Table 6: McCrary (2008) Test for Quasi-Random Assignment

Dependent Variable = Prob Mass of 0.05 Star Bin	
Treatment (0.05 star interval above rounding threshold)	0.018
	(0.017)
Observations	33

Note: Dependent variable is the probability mass of observations in each 0.05 rating interval. The treatment variable indicates intervals that are just above a rounding threshold.

Table 7: OLS Regression: Impact on the Speed of Filling an Appointment

Dependent Variable: Number of days between the appointment date and the date the appointment got filled

	(1)	(2)	(3)	(4)	(5)
Avg. Overall Rating	0.279***	0.266***	0.250***	0.296***	0.275***
	(0.088)	(0.091)	(0.090)	(0.074)	(0.071)
No. Of Patient Reviews (Standardized~(0,1))		0.027	0.029	-0.003	-0.038
		(0.027)	(0.027)	(0.023)	(0.025)
Text Review Variables					
Bad Key Words (%)			0.014	-0.007	-0.031
			(0.058)	(0.052)	(0.049)
Good Key Words (%)			0.006	0.013	0.006
			(0.012)	(0.010)	(0.009)
Physician Profile Variables					
Female				0.234***	0.223***
				(0.061)	(0.061)
Us Medical Degree				0.057	-0.005
				(0.060)	(0.057)
Affiliated To Teaching Hospital				0.179***	0.278***
				(0.058)	(0.059)
Any Award Or Publication				0.057	0.010
				(0.063)	(0.059)
Speaks Spanish				-0.113*	-0.119**
				(0.060)	(0.059)
Appointment Day of the Week Dummy				x	x
Appointment Time of the Day Dummy				x	x
Zip Level Variables					x
Constant	1.050***	1.109***	1.137***	0.551	0.783
	(0.404)	(0.414)	(0.410)	(0.339)	(1.623)
Observations	90,420	90,420	90,420	90,420	90,420
No. of Physicians	395	395	395	395	395
Adj R2	0.004	0.004	0.004	0.094	0.109

Note: Standard errors are in parentheses and are clustered for physician IDs. ***, **, * denote significance at 1%, 5%, and 10% level respectively. The unit of observation is an appointment that gets filled. Bad (Good) key words are expressed as percentage of total text review word count. Zip level demographic variables are from American Community Survey (2011). The zip level demographic variables included are Hispanic (%), White (%), Asian (%), Age 21-64 (%), Age 65+ (%), Works from Home (%), Median Household Income (Standardized~(0,1)), Married-Couple Families (%), Average Family Size, and Same Residence as 1 year ago (%).

Table 8: Regression Discontinuity Analysis: Impact on the Speed of Filling an Appointment, Bandwidth= 0.1

Dependent Variable: Number of days between the appointment date and the date the appointment got filled

	(1)	(2)	(3)	(4)	(5)
Threshold Dummy	0.15	0.15	0.13	0.16*	0.18**
	(0.112)	(0.111)	(0.109)	(0.082)	(0.084)
Avg. Overall Rating	x	x	x	x	x
No. of Patient Reviews		x	x	x	x
Text Review Variables			x	x	x
Physician Profile Variables				x	x
Appointment Day of the Week Dummy				x	x
Appointment Time of the Day Dummy				x	x
Zip Level Variables					x
Observations	18,866	18,866	18,866	18,866	18,866
No. of Physicians	123	123	123	123	123
Adj R2	0.002	0.002	0.010	0.117	0.146

Note: Standard errors are in parentheses and are clustered for physician IDs. ***, **, * denote significance at 1%, 5%, and 10% level respectively. All physicians with at least 5 reviews are included in the regression. Regressions include all observations within 0.1 stars of a discontinuity.

Table 9: OLS Regression: Impact on the Supply of New Appointments by the Physicians

Dependent Variable: Supply of Appointments as a Proportion of Avg. Supply in Last 7 Days

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg. Prob. of Filling an Appointment in the Last 7 days	0.090***	0.088***	0.087***	0.087***	0.060***	0.063***	0.063***	0.066***
	(0.023)	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Avg. Overall Rating		0.009	0.008	0.007	0.007	0.015		
		(0.020)	(0.020)	(0.021)	(0.020)	(0.021)		
No. Of Patient Reviews (Standardized~(0,1))			0.003	0.003	0.005	0.004		
			(0.010)	(0.010)	(0.009)	(0.010)		
Text Review Variables								
Bad Key Words (%)				0.002	0.000	0.002		
				(0.010)	(0.010)	(0.011)		
Good Key Words (%)				0.000	0.002	0.001		
				(0.002)	(0.002)	(0.002)		
Physician Profile Variables								
Female					0.013	0.011	0.012	0.009
					(0.016)	(0.016)	(0.016)	(0.016)
US Medical Degree					0.017	0.018	0.019	0.020
					(0.016)	(0.017)	(0.015)	(0.017)
Affiliated to Teaching Hospital					-0.008	-0.005	-0.006	-0.003
					(0.015)	(0.015)	(0.015)	(0.015)
Any Award or Publication					-0.006	-0.009	-0.007	-0.009
					(0.017)	(0.017)	(0.017)	(0.017)
Speaks Spanish					-0.019	-0.020	-0.018	-0.019
					(0.015)	(0.015)	(0.015)	(0.015)
Appointment Day of the Week Dummy					x	x	x	x
Zip Level Variables						x		x
Constant	1.003***	0.961***	0.968***	0.968***	0.726***	0.244	0.765***	0.299
	(0.012)	(0.088)	(0.088)	(0.093)	(0.093)	(0.458)	(0.031)	(0.446)
Observations	11,524	11,524	11,524	11,524	11,524	11,524	11,524	11,524
No. of Physicians	397	397	397	397	397	397	397	397
Adj R2	0.003	0.003	0.003	0.003	0.035	0.036	0.035	0.036

Note: Standard errors are in parentheses and are clustered for physician IDs. ***, **, * denote significance at 1%, 5%, and 10% level respectively.

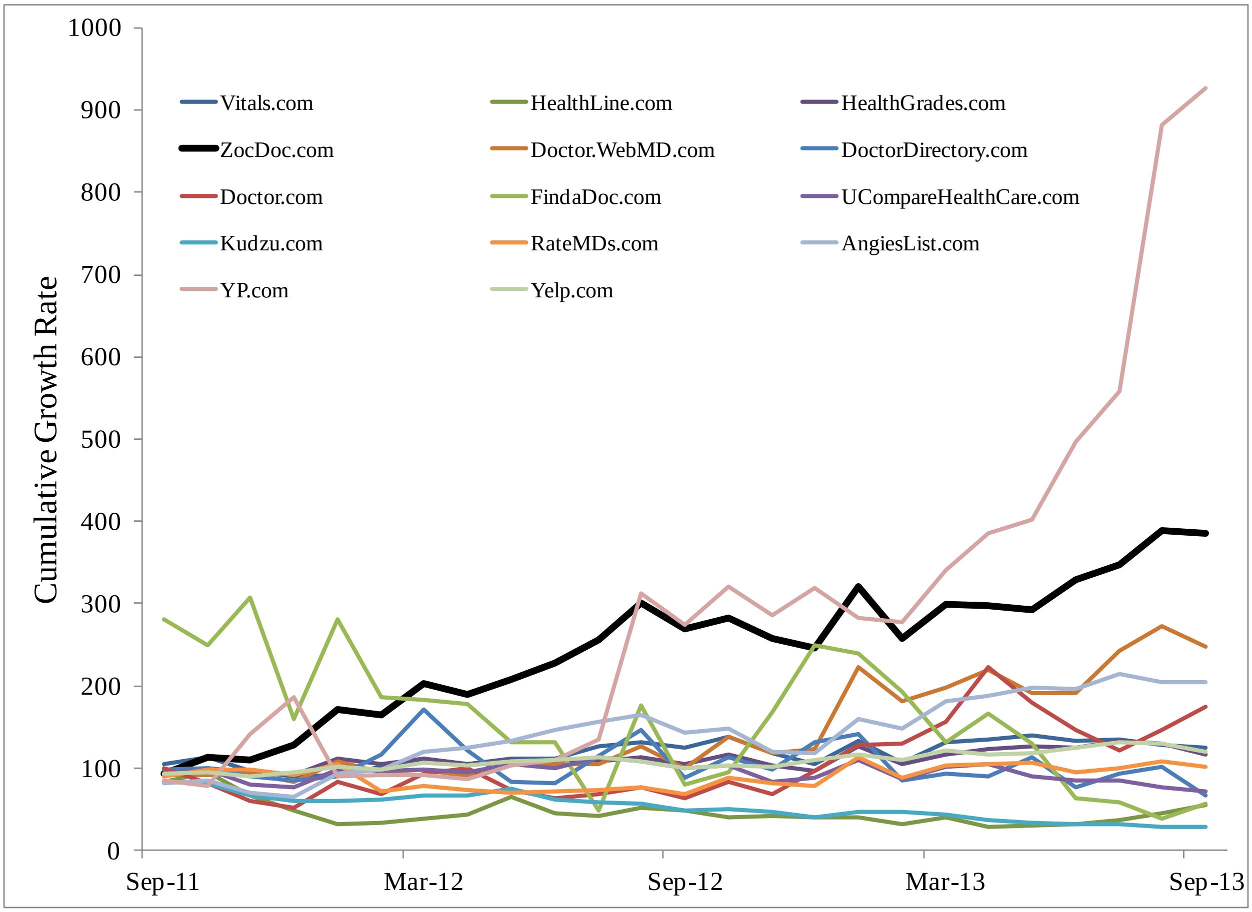
Table 10: OLS Regression: Impact on the Supply of New Appointments by the Physicians

Dependent Variable: Supply of Appointments as a Proportion of Avg. Supply in Last 14 Days

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg. Prob. of Filling an Appointment in the Last 14 days	0.063***	0.062***	0.062***	0.064***	0.038*	0.041*	0.039*	0.042*
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.023)	(0.022)	(0.022)
Avg. Overall Rating		0.007	0.009	0.008	0.008	0.011		
		(0.022)	(0.022)	(0.024)	(0.023)	(0.023)		
No. Of Patient Reviews (Standardized~(0,1))			-0.004	-0.004	0.000	-0.002		
			(0.009)	(0.009)	(0.008)	(0.009)		
Text Review Variables								
Bad Key Words (%)				0.005	0.005	0.006		
				(0.010)	(0.011)	(0.011)		
Good Key Words (%)				0.001	0.002	0.002		
				(0.002)	(0.002)	(0.002)		
Physician Profile Variables								
Female					0.006	0.006	0.003	0.003
					(0.016)	(0.016)	(0.015)	(0.015)
US Medical Degree					0.011	0.009	0.013	0.010
					(0.016)	(0.017)	(0.015)	(0.017)
Affiliated to Teaching Hospital					-0.020	-0.020	-0.020	-0.021
					(0.014)	(0.015)	(0.014)	(0.015)
Any Award or Publication					-0.003	-0.004	-0.003	-0.004
					(0.016)	(0.017)	(0.016)	(0.016)
Speaks Spanish					-0.023	-0.022	-0.022	-0.021
					(0.015)	(0.015)	(0.015)	(0.015)
Appointment Day of the Week Dummy					x	x	x	x
Zip Level Variables						x		x
Constant	1.005***	0.974***	0.964***	0.960***	0.744***	0.453	0.795***	0.501
	(0.013)	(0.100)	(0.101)	(0.106)	(0.106)	(0.457)	(0.031)	(0.448)
Observations	10,245	10,245	10,245	10,245	10,245	10,245	10,245	10,245
No. of Physicians	397	397	397	397	397	397	397	397
Adj R2	0.00182	0.00176	0.00173	0.00167	0.0403	0.0406	0.0403	0.0405

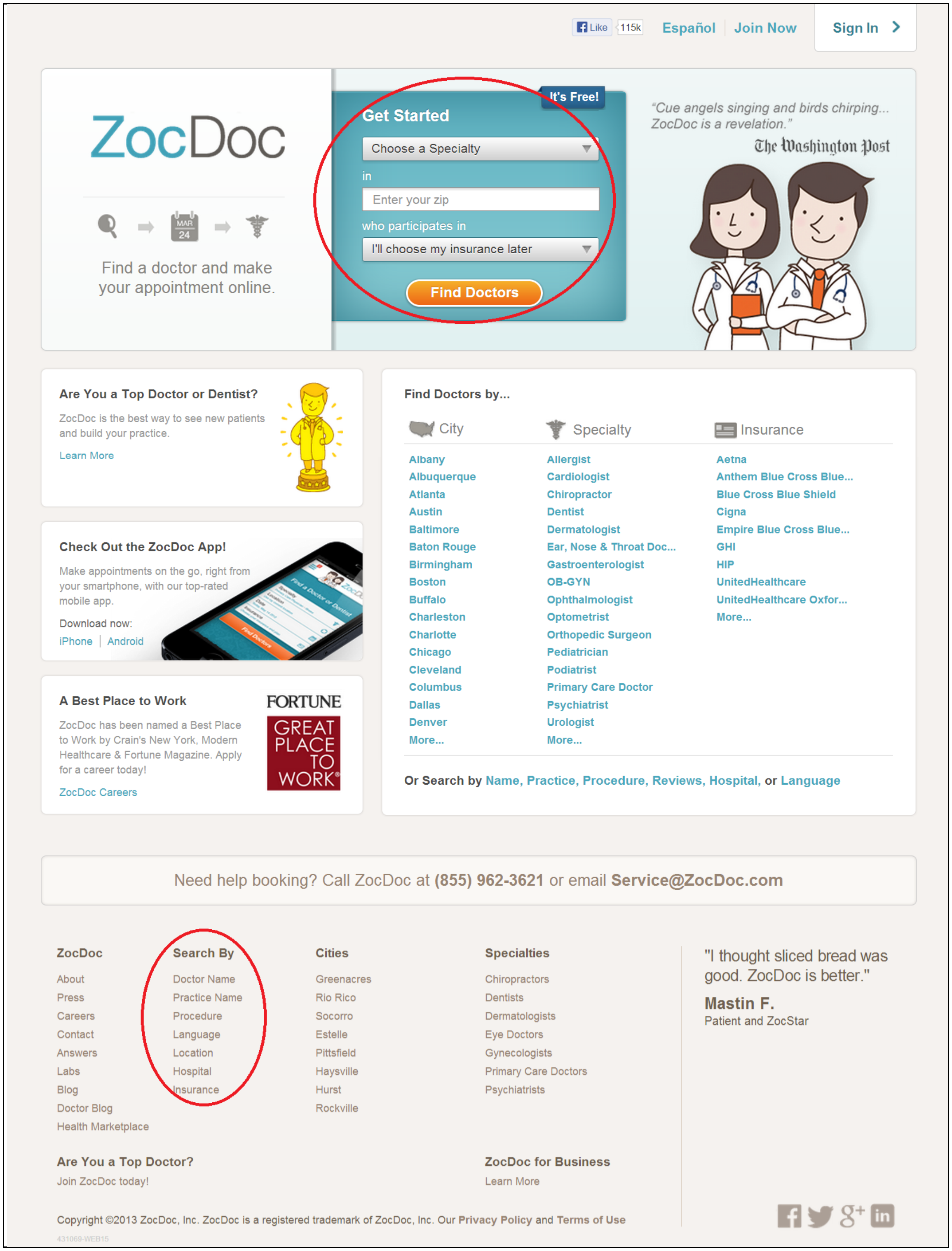
Note: Standard errors are in parentheses and are clustered for physician IDs. ***, **, * denote significance at 1%, 5%, and 10% level respectively.

Figure 1: Cumulative Monthly Growth Rate in *Number of Unique Visitors* to the Top 14 Most Frequently Visited Websites to Find Doctors as of October 18, 2013



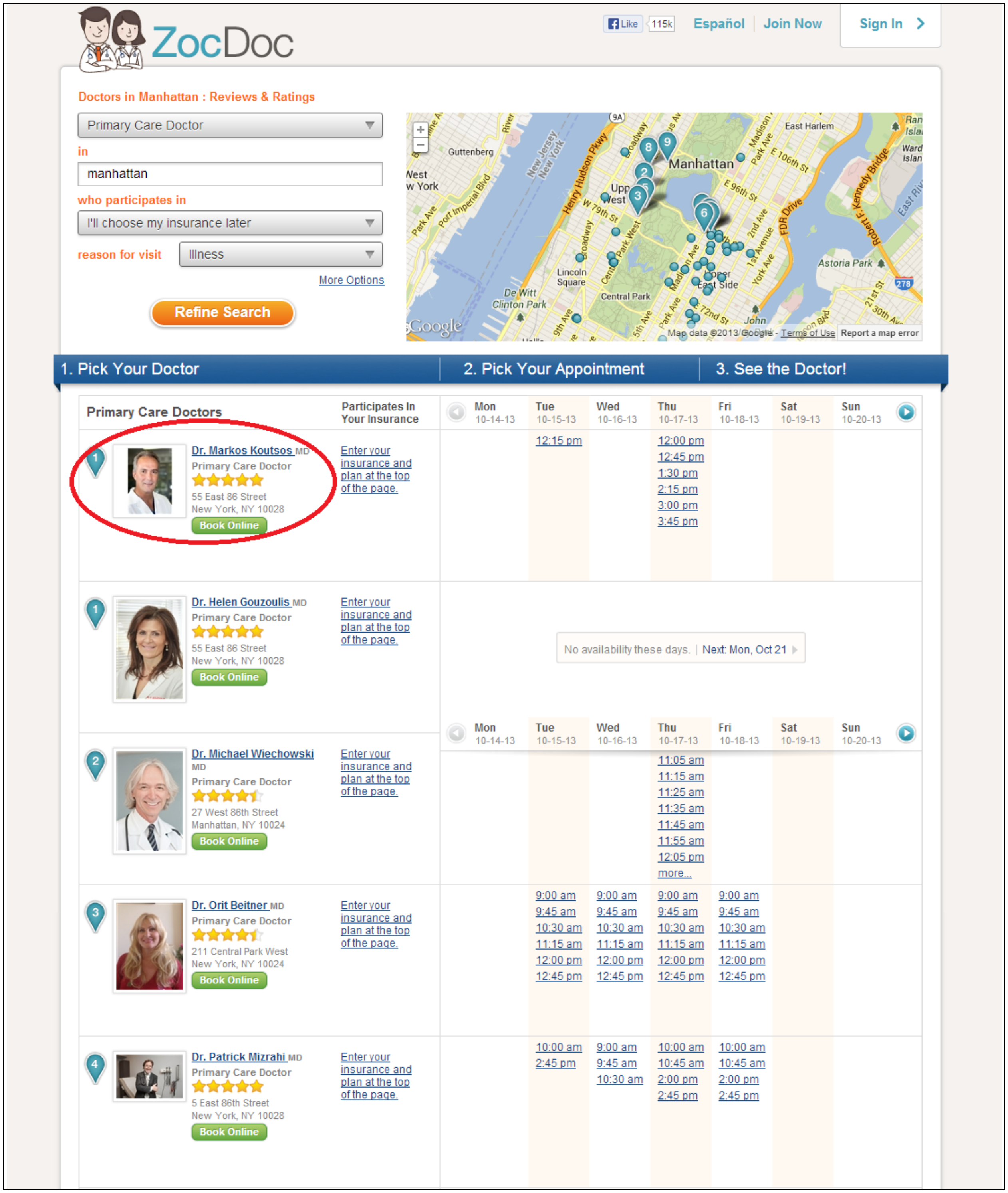
Note: On October 18, 2013 we searched for the term *Find Doctors* using Google, Bing, and Yahoo. We picked up all the website names that came up on the first page after the search, that allow users to search for physicians. This exercise gave us 11 websites excluding Yelp.com, AngiesList.com and Kudzu.com. We include these three websites following Kadry et al. (2011). Using Compete.com, a website traffic analysis service, we compare the number of unique visitors to these websites, beginning September, 2011. Figure 1 plots the cumulative monthly change in the number of unique visitors to these websites since September, 2011. ZocDoc.com ranks 2nd, after yellow pages, in the cumulative growth rate of number of unique visitors to the website.

Figure 2: www.ZocDoc.com Home Page



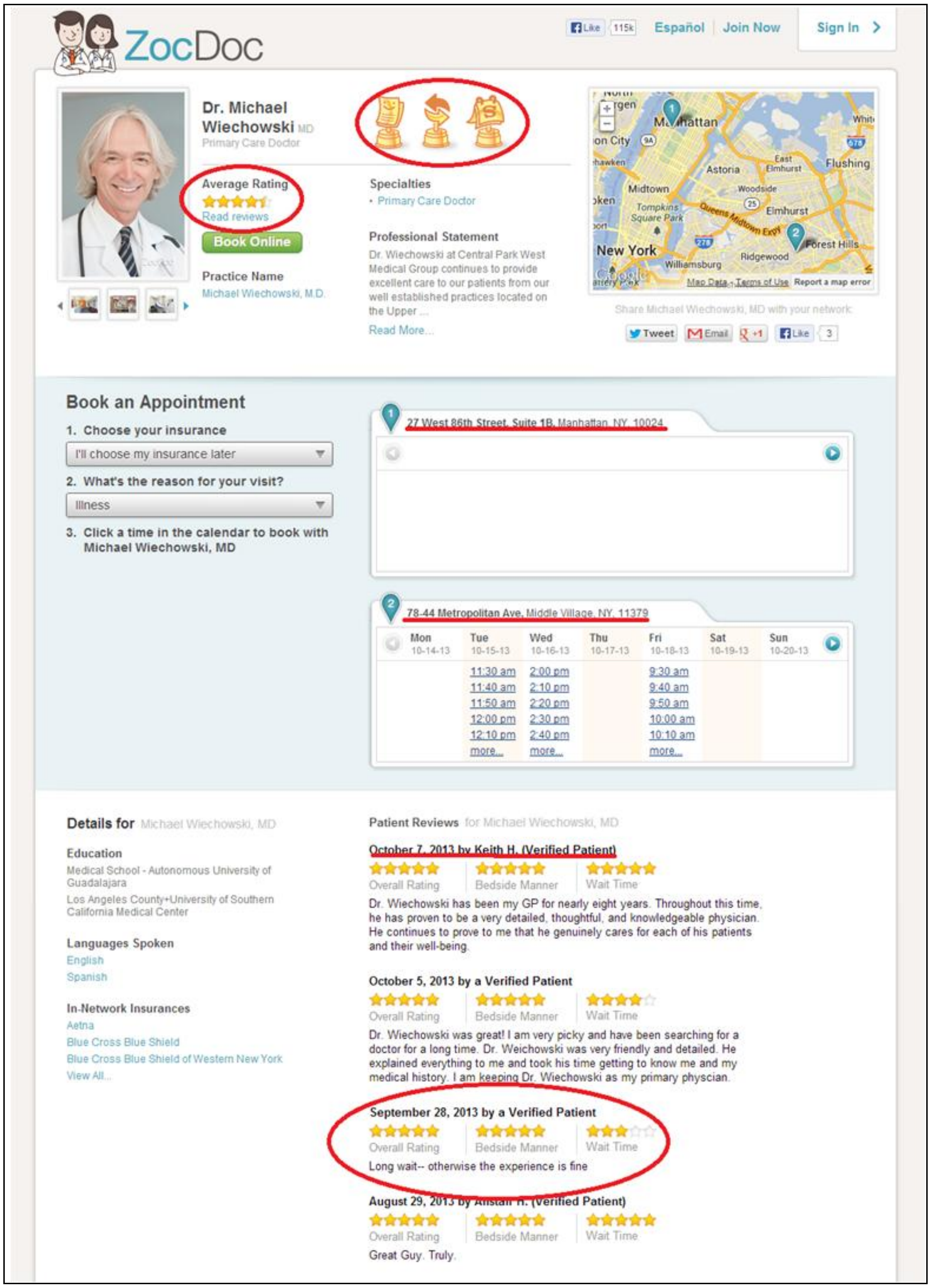
Note: This figure shows the home page of www.ZocDoc.com. On this page the website enables patients to search for physicians by specialty, location, insurance, practice name, procedure, hospital, and language. The search related features of the webpage are encircled in red.

Figure 3: Physician Search Result: Physician and Appointment Options



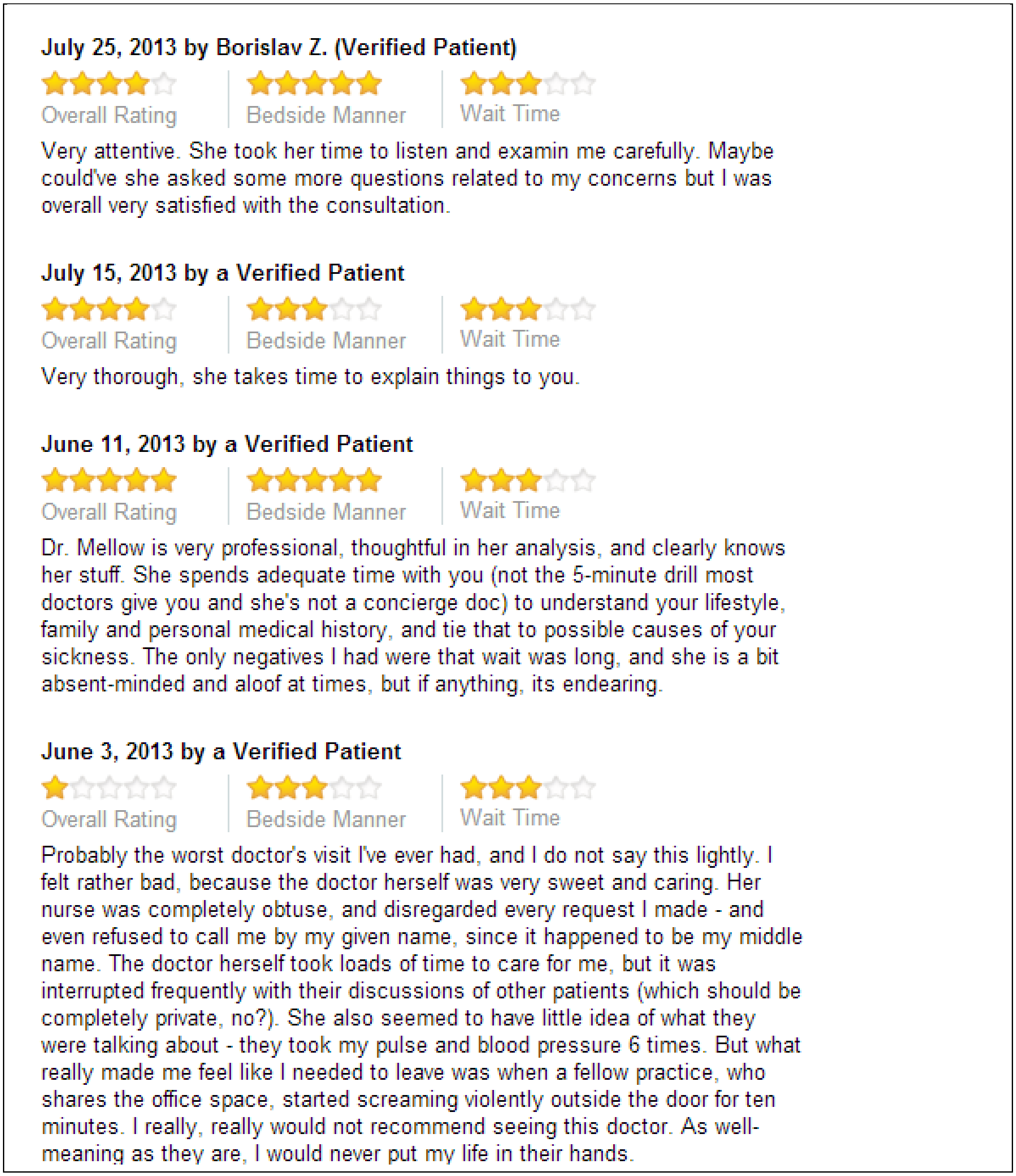
Note: The above figure shows the first four physicians from the list of primary care physicians, that is displayed after a search of primary care physician, in Manhattan. Physician's address and rounded average ratings (stars) are prominently displayed next to his picture (see the section encircled in red ink for an example). More stars means higher rating of the physician. Also displayed are the appointment slots available during the current week.

Figure 4: A Typical Physician's Profile Page



Note: This figure shows a typical doctor's profile page. The rounded average rating are displayed next to his picture (encircled in red ink). Also displayed at the top of the page are the physician awards given by ZocDoc to inform the patients about the physician's strength on ZocDoc (encircled in red ink). These awards are explained in further detail in Table 6. The physician's specialty, practice name, education details, hospital affiliations, languages spoken, and a complete list of insurances accepted are also displayed. Details of each patient review—date, and patient name if disclosed by the patient— are also displayed (underlined in red ink). After the appointment a patient can rate the physician for overall rating, bedside manner, as well as wait time (section encircled in red). The patient can also leave a text review to describe their experience in detail. All this information is displayed on the physician's profile page.

Figure 5: An Example of Patient Reviews



July 25, 2013 by Borislav Z. (Verified Patient)

Overall Rating | Bedside Manner | Wait Time

Very attentive. She took her time to listen and examin me carefully. Maybe could've she asked some more questions related to my concerns but I was overall very satisfied with the consultation.

July 15, 2013 by a Verified Patient

Overall Rating | Bedside Manner | Wait Time

Very thorough, she takes time to explain things to you.

June 11, 2013 by a Verified Patient

Overall Rating | Bedside Manner | Wait Time

Dr. Mellow is very professional, thoughtful in her analysis, and clearly knows her stuff. She spends adequate time with you (not the 5-minute drill most doctors give you and she's not a concierge doc) to understand your lifestyle, family and personal medical history, and tie that to possible causes of your sickness. The only negatives I had were that wait was long, and she is a bit absent-minded and aloof at times, but if anything, its endearing.

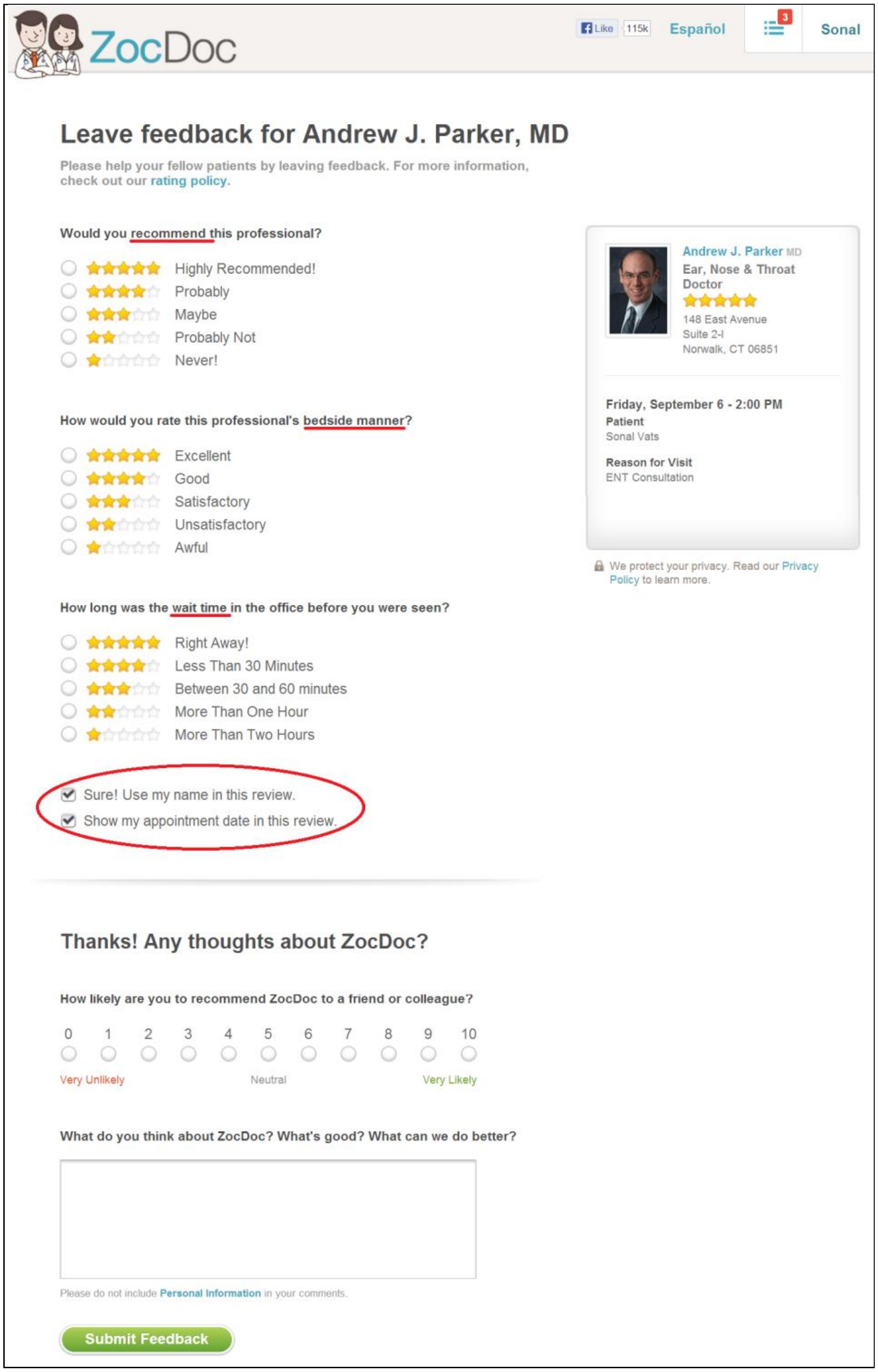
June 3, 2013 by a Verified Patient

Overall Rating | Bedside Manner | Wait Time

Probably the worst doctor's visit I've ever had, and I do not say this lightly. I felt rather bad, because the doctor herself was very sweet and caring. Her nurse was completely obtuse, and disregarded every request I made - and even refused to call me by my given name, since it happened to be my middle name. The doctor herself took loads of time to care for me, but it was interrupted frequently with their discussions of other patients (which should be completely private, no?). She also seemed to have little idea of what they were talking about - they took my pulse and blood pressure 6 times. But what really made me feel like I needed to leave was when a fellow practice, who shares the office space, started screaming violently outside the door for ten minutes. I really, really would not recommend seeing this doctor. As well-meaning as they are, I would never put my life in their hands.

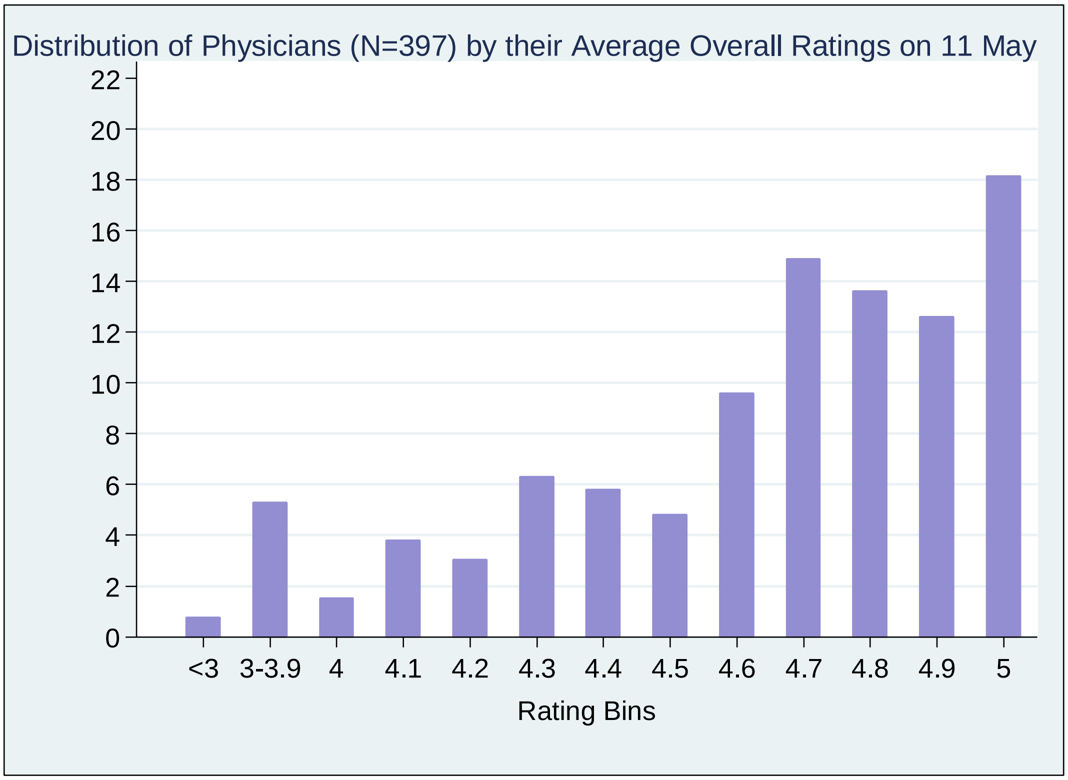
Note: This figure shows a snapshot of reviews for Dr. Ellen Mellow, MD. She is a primary care physician practicing in Manhattan. The figure shows the range of ratings and the detailed reviews left by patients. This webpage was accessed on October 14, 2013.

Figure 6: The Review Process



Note: After the appointment ZocDoc emails a thank you note to the patient encouraging the patient to leave a feedback. The above figure shows the feedback page. The patient can rate the physician on a scale of 1-5 under three categories—would you recommend this professional, bedside manner, and wait time (see underlined in red ink). ZocDoc also asks permission to use patient's name and appointment date in the review that will be displayed on the physician's webpage (see section encircled in red ink).

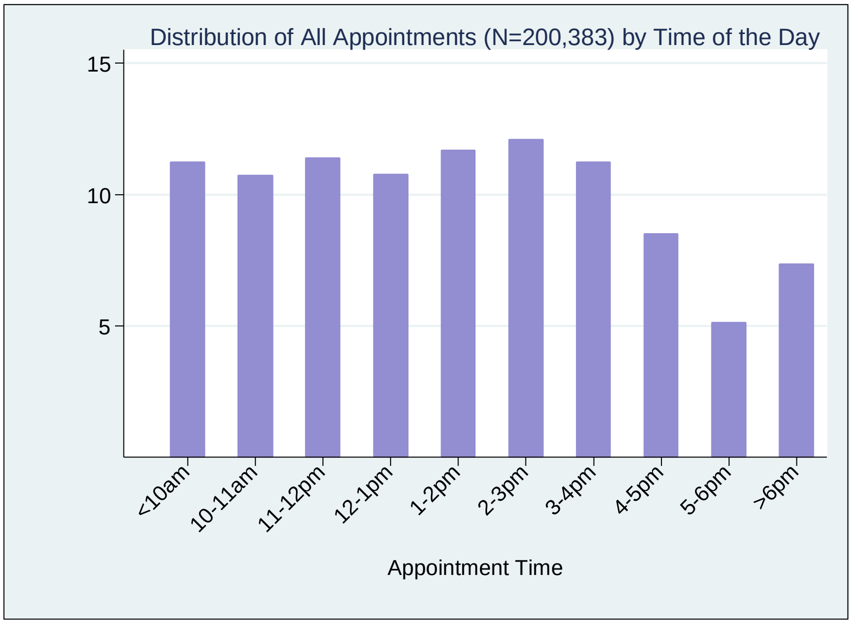
Figure 7: Distribution of Physicians (N=397) by their Average Overall Ratings



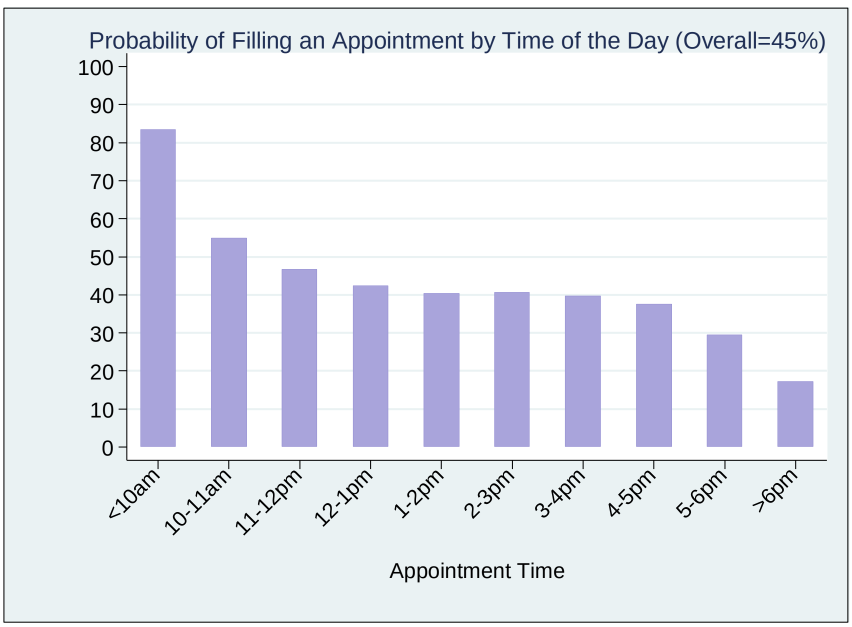
Note: Figure 7 reports the distribution of physicians in our data by their average overall ratings, as of May 11, 2013. The figure is based on a distribution of ratings on the last day of our data collection exercise, the average rating for individual physicians does change over the course of our data collection, as new reviews are available, however the distribution of ratings on different days in our sample are quantitatively similar. The y axis is the percentage of physicians with a given rating. Thus a doctor that has 2 reviews and average rating of 4 has the same weight as another doctor that has 20 reviews with rating of 4. Therefore, in the sample around 18% of the doctors have a perfect rating of 5.

Figure 8: Distribution of All Appointments (N=200,383) by Time of the Day

Panel A: Distribution of All the posted Appointments by Time of the Day

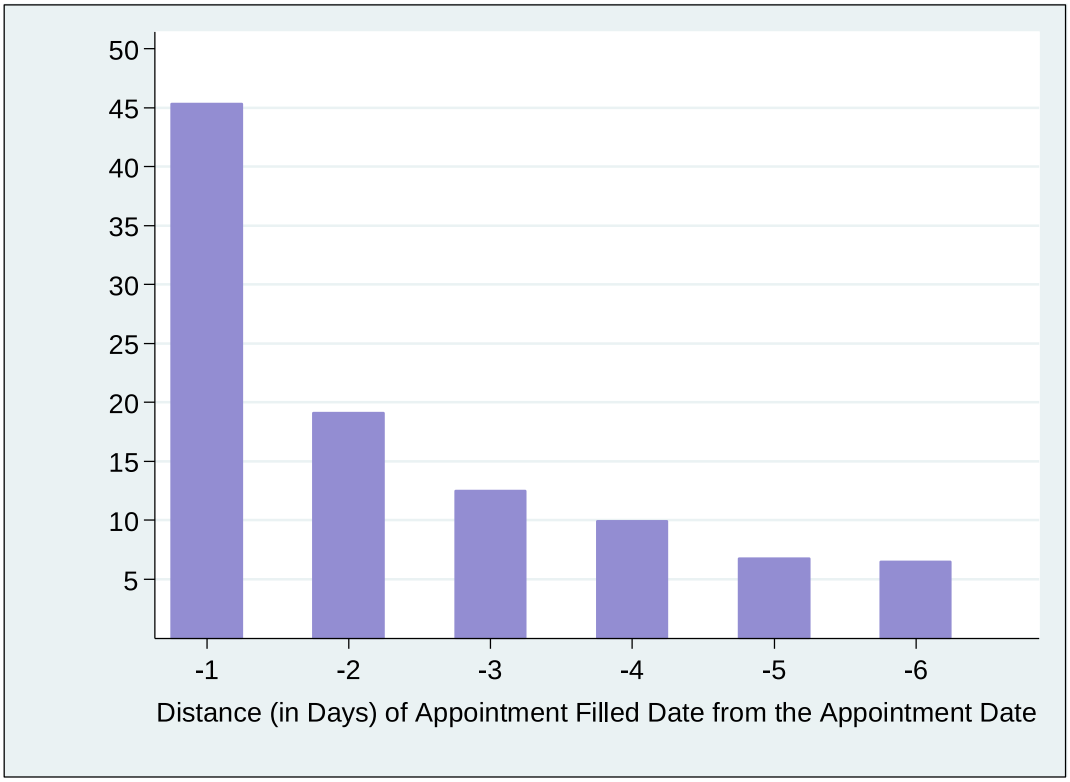


Panel B: Probability of Filling an Appointment by Time of the Day (Overall=45%)



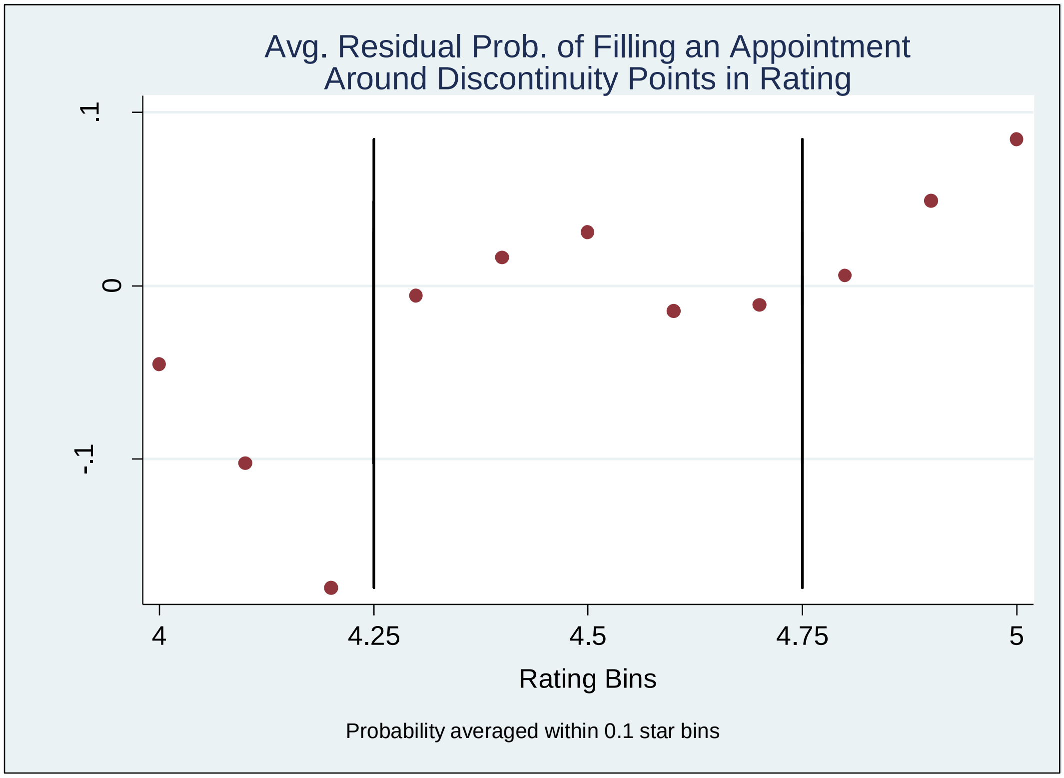
Note: Panel A reports the distribution of all the listed appointments by the time of the day, for the period February 24, 2013 to May 11, 2013. Panel B reports the distribution of the probability of filling an appointment by the time of the day.

Figure 9: Distribution of Filled Appointments (N=90,539) by the Distance of Appointment Filled Date from the Appointment Date



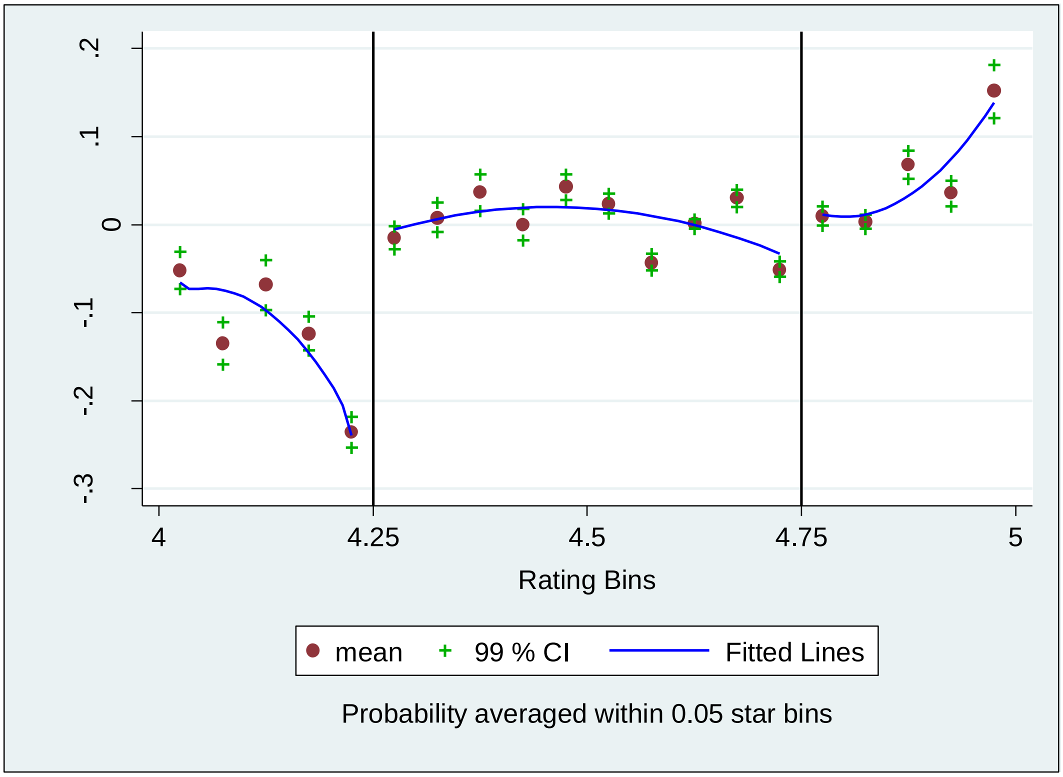
Note: This figure reports the distribution of distance in days of the appointment filled date from the appointment date. A distance of -1 implies that the appointment was filled within 24 hours of the appointment date. Overall, 45 percent of all appointments made available on ZocDoc during February 24, 2013 to May 11, 2013 get filled.

Figure 10: Discontinuous Changes in Probability of Filling an Appointment Around the Discontinuity Points, Binwidth = 0.1



Note: The residuals are from a marginal probit regression with dependent Variable = 1 (if appointment filled); 0 (open appointments), based on regression (5) in table 4. All physicians with at least 5 reviews are included in the regression. The residuals are averaged within 0.1 star bins, 4.25 and 4.75 are the two discontinuity points. We see a sharp jump at 4.25 but not much effect at 4.75.

Figure 11: Discontinuous Changes in Probability of Filling an Appointment Around the Discontinuity Points, Binwidth = 0.05



Note: The residuals are from a marginal probit regression with dependent Variable = 1 (if appointment filled); 0 (open appointments), based on regression (5) in table 4. All physicians with at least 5 reviews are included in the regression. The residuals are averaged within 0.05 star bins, 4.25 and 4.75 are the two discontinuity points. We see a sharp jump at 4.25 but not much effect at 4.75. The figure also shows 99% bootstrapped confidence intervals. Local polynomial regression is used to fit the smooth lines.

Appendix: Data Summary Additional Tables

Table A.1: Distribution of Physicians (N=391) by Practice Size

Practice Size	Frequency (%)
1	63
2	10
3	7
4	3
5	4
6	5
7	2
9	2
16	4

Table A.2: Distribution of Physicians by ZocDoc Badges Received

Badges	Population (%)
Rapid Registration	51
Scheduling Hero	60
See You Again	71
Speedy Response	73

Rapid registration: Provides digital registration forms. See You Again: Large number of ZocDoc patients book repeatedly with the physician. Speedy Response: Physicians who confirm their appointments within one business hour. Scheduling Hero: Physicians who keep their schedule up-to-date.

Figure A.3: Distribution of Physicians by their Average Bedside Manner, and Average Wait Time Ratings